

# CSCI 550 - Project 2

Eliot Liucci, Eric Folsom, Nick Clausen, Christal O'Connell

2024-11-08

## 1 Executive Summary

This project aims to determine the most optimal information to collect on real estate listings in the Chicago area. This was done by scraping data from 2013 to 2019 and collecting variables relating to the area of a listing and physical properties of the listing. When searching for the variables that best explain sale price in the Chicago area, exploratory data analysis found that the size of the listing, number of rooms present, estimated value, and additional quality of life features like a garage or fireplaces are the best predictors. To further determine best predictors, various models were fit and compared. We formally recommend using the estimate of the value of land a listing was built on and the estimate of the building itself as the main factors for determining how much a listing will sell for.

## 2 Data Preprocessing and Exploration

### 2.1 Data Cleaning

The data received had a few issues that needed to be dealt with. First of all, the `Description` variable contained pieces of key information that were extracted (number of bathrooms, number of bedrooms, total number of rooms, and sell date). Additionally, Area, Sub-Area, Block, Parcel, and Multicode were parsed from the PIN variable.

```
# Extracting important information from descriptions
sell_date = as.numeric(0)
rooms = as.numeric(0)
bedrooms = as.numeric(0)
baths = as.numeric(0)

# Takes a minute to run, not too bad though
for(i in 1:nrow(data)){
    sell_date[i] = str_split(
        str_split(data$Description[i], "sold on ")[[1]][2],
        ", is a")[[1]][1]
    rooms[i] = str_extract_all(
        str_split(data$Description[i], "total of ")[[1]][2],
        "\\d")[[1]][1]
    bedrooms[i] = str_extract_all(
        str_split(data$Description[i], "total of ")[[1]][2],
        "\\d")[[1]][2]
    baths[i] = str_split(
        str_split(data$Description[i], "bedrooms, and ")[[1]][2],
        " of which are bathrooms")[[1]][1]
    Area[i] = substring(data$PIN[i], first = 1, last = 2)
    Sub_Area[i] = substring(data$PIN[i], first = 3, last = 4)
    Block[i] = substring(data$PIN[i], first = 5, last = 6)
    Parcel[i] = substring(data$PIN[i], 7, 8)
    Multicode[i] = substring(data$PIN[i], 9, 12)
}
```

Once these variables were extracted, the `Description` variable was dropped from the data set. We noticed some houses with strange recording like “42 bathrooms and 7 rooms”, so we dropped any listings where the number of bedrooms and number of bathrooms was greater than the total recorded number of rooms.

```
# Adding features of descriptions, removing descriptions
data = data %>%
    mutate(
        Sell_Date = mdy(sell_date),
```

```

Rooms = as.numeric(rooms),
Bedrooms = as.numeric(bedrooms),
Baths = as.numeric(baths)
) %>%
select(-Description)

# Removing rows where num bathrooms/bedrooms exceeds number of rooms
data = data %>%
filter(Bedrooms < Rooms | Baths < Rooms)

```

Next, we dropped any listings with a missing value in at least one of the variables.

```

# Removing rows with at least 1 missing value
data = data %>%
drop_na()

```

We also wanted to deal with outliers, so a function was written that would identify a listing as an outlier if it was greater than 3 standard errors away from the mean value and used this to remove outliers for variables where the maximum value was significantly higher than the 3rd quartile.

```

# Filtering extreme observations
is_outlier = function(x){
  result = abs(x - mean(x)) > 3*sd(x)
  return(result)
}

# Removing outliers for variables where max() is greater than q3()
data = data %>%
filter(!is_outlier(`Sale Price`),
       !is_outlier(`Land Square Feet`),
       !is_outlier(Baths),
       !is_outlier(`Lot Size`),
       !is_outlier(`Town and Neighborhood`),
       !is_outlier(`Age Decade`),
       !is_outlier(`Age`),
       !is_outlier(`Estimate (Land)`),
       !is_outlier(`Estimate (Building)`),
       !is_outlier(`Building Square Feet`),
       !is_outlier(`Other Improvements`))

```

Finally, we removed all spaces from variable names and replaced them with underscores.

```

# Removing Spaces
data = data %>%
  rename(Property_Class = `Property Class`,
         Neighborhood_Code = `Neighborhood Code`,
         Land_Square_Feet = `Land Square Feet`,
         ...
         Age_Decade = `Age Decade`,
         Neighborhood_Code_Mapping = `Neighborhood Code (mapping)`,
         Town_and_Neighborhood = `Town and Neighborhood`,
         )

```

This cleaned data set was written as `data_cleaned.csv` so it could easily be reloaded for the remainder of the analysis.

```

# Save cleaned data
write_csv(data, "data_cleaned.csv")

```

## 2.2 Exploration of Data

Within the data, latitude and longitude coordinates were provided for each listing. A map of the sale price of listings is overlaid on a satellite map of the region (Figure 1). Here, it can be seen that a lot of the higher price listings are on the water, with sale price generally decreasing the more in-land the listing is.

```

# Spatial Map of Sale Price
ggmap(Map, darken = c(0.1, "white")) +
  geom_polygon(data = cook_map, aes(x = long, y = lat),
               fill = NA, color = "orange") +
  geom_point(data = data,
             aes(x = Longitude,
                 y = Latitude,
                 color = Sale_Price),
             size = 0.02,
             alpha = 0.75) +
  scale_color_gradient(low = "#6fe7f7", high = "#890000") +
  labs(x = "Longitude", y = "Latitude", color = "Sale Price ($)")

```

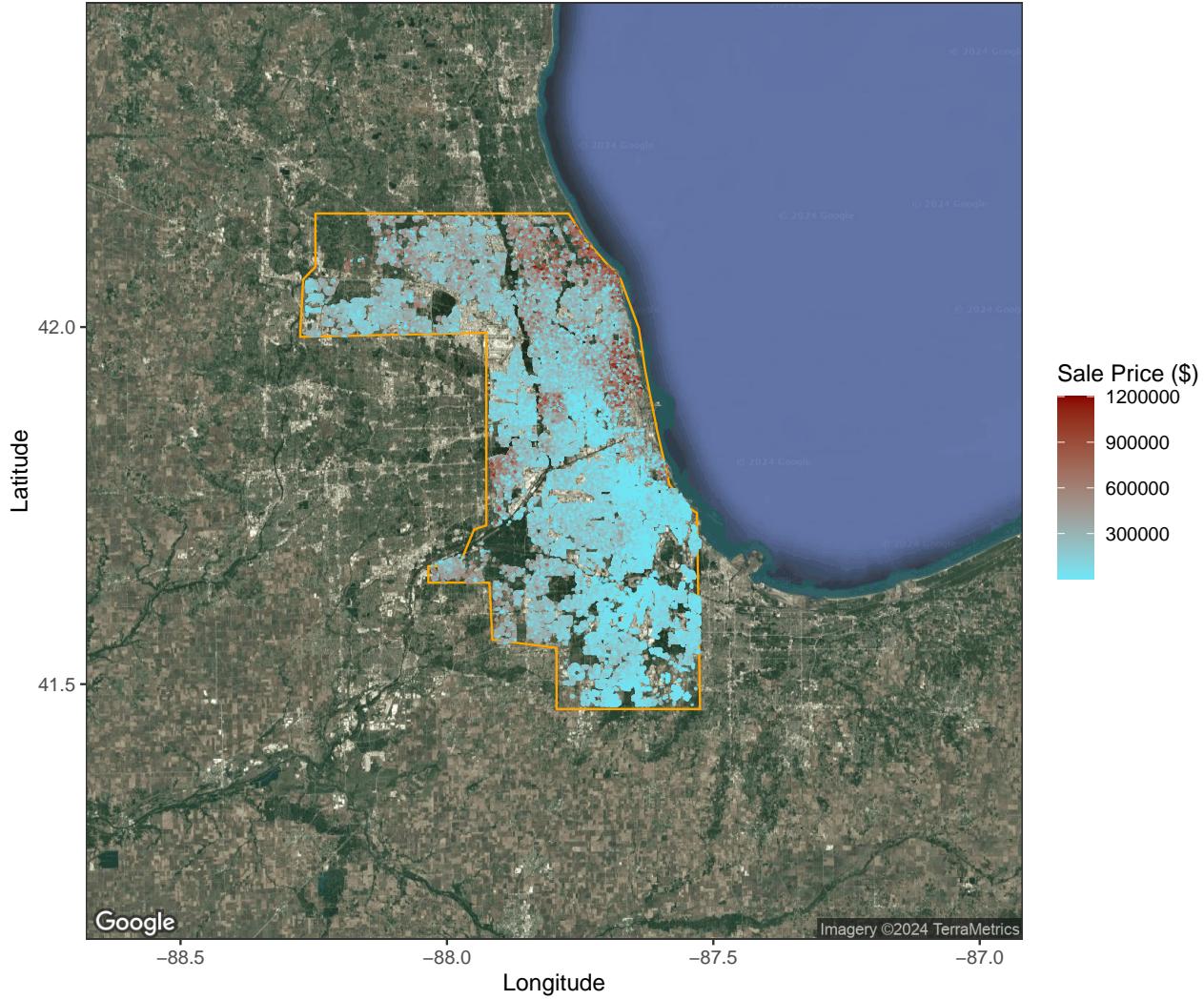


Figure 1: A spatial map of the sale prices over the region.

Multiple boxplots were created for all of the variables pertaining to a garage against the response (Figure 2). As the first garage increases in size, so too does the sale price. Having a garage attached to the building (`Garage_#_Attachment = 1`) is also associated with a higher sale price for both garage 1 and garage 2. Higher quality materials (larger values of `Garage_#_Material`) is associated with higher sale prices too.

```
# Plotting Against Garage Variables
data %>%
  select(Sale_Price,
         Garage_1_Area,
         Garage_1_Size,
         Garage_1_Attachment,
         Garage_1_Material,
         Garage_2_Area,
         Garage_2_Size,
```

```

Garage_2_Attachment,
Garage_2_Material) %>%
pivot_longer(cols = 2:9, names_to = "Variable", values_to = "Value") %>%
ggplot(aes(x = factor(Value), y = Sale_Price, group = Value)) +
geom_boxplot() +
facet_wrap(~Variable, scales = "free_x", nrow = 2) +
labs(x = " ")

```

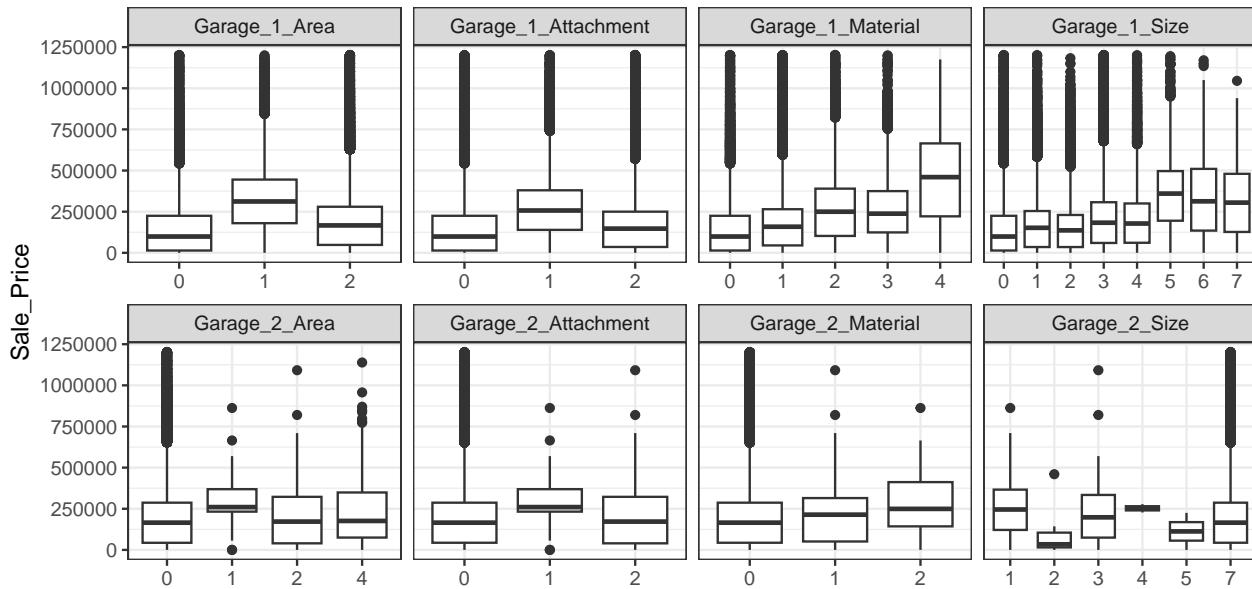


Figure 2: A series of boxplots for all garage variables against sale price.

When comparing sale price to variables related to the physical property, it can be noted that for the `Apartments` variable, there is large variability in the “0” group, which may be due to non-apartment buildings being more expensive (Figure 3). Sale price is generally the same across attic types, porch groups, and design plans. Sale price appears to increase as the number of fireplaces increases. Additionally, sale price is higher for listings with cathedral ceilings. The `Property_Class` variable appears to have equal variability in sale price for all classes except “209”.

```

data %>%
  select(`Sale_Price`,
         `Property_Class`,
         `Apartments`,
         `Basement`,
         `Attic_Type`,
         `Design_Plan`,
         `Cathedral_Ceiling`,
         Fireplaces,

```

```

Porch) %>%
pivot_longer(cols = 2:9, names_to = "Variable", values_to = "Value") %>%
ggplot(aes(x = factor(Value), y = Sale_Price, group = Value)) +
geom_boxplot() +
facet_wrap(~Variable, scales = "free_x", nrow = 2) +
labs(x = " ")

```

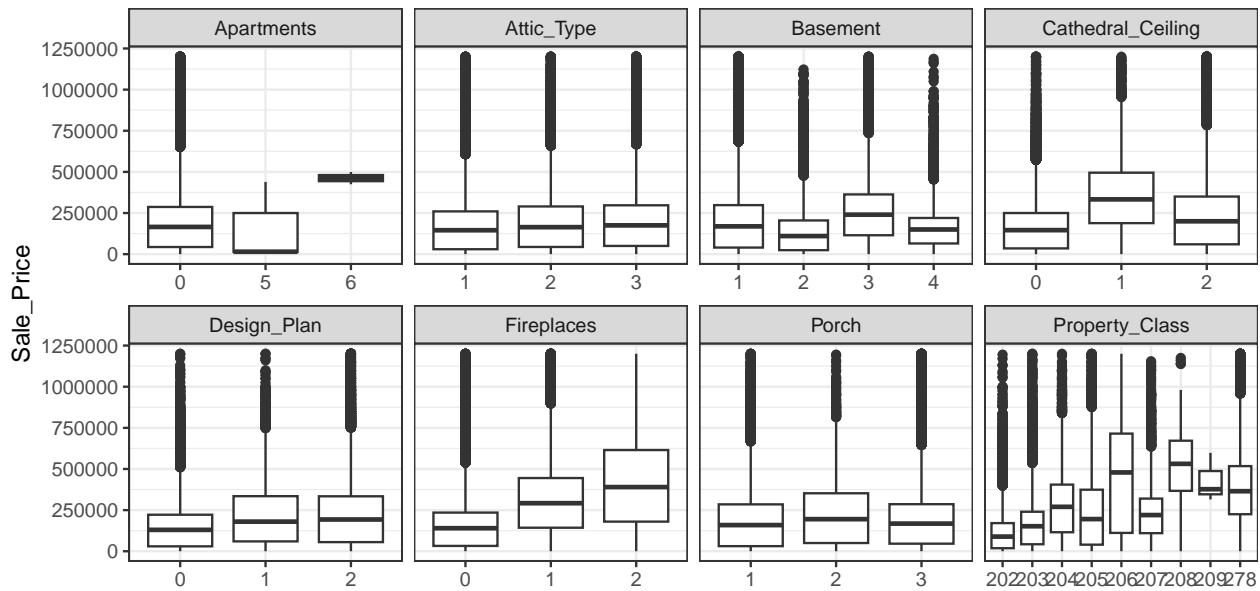


Figure 3: A series of boxplots for variables related to the property itself.

Additional boxplots were created for the number of rooms in each listing (Figure 4). For all room variables, there is generally an increase in sale price as the number of rooms increases. However, the sale price for listings with 1 room is higher, on average, than all other room groups. The same goes for listings with 0 bedrooms.

```

# Plotting Against Room Variables
data %>%
  select(`Sale_Price`,
         `Bedrooms`,
         `Baths`,
         `Rooms`) %>%
pivot_longer(cols = 2:4, names_to = "Variable", values_to = "Value") %>%
ggplot(aes(x = factor(Value), y = Sale_Price, group = Value)) +
geom_boxplot() +
facet_wrap(~Variable, scales = "free_x") +
labs(x = " ")

```

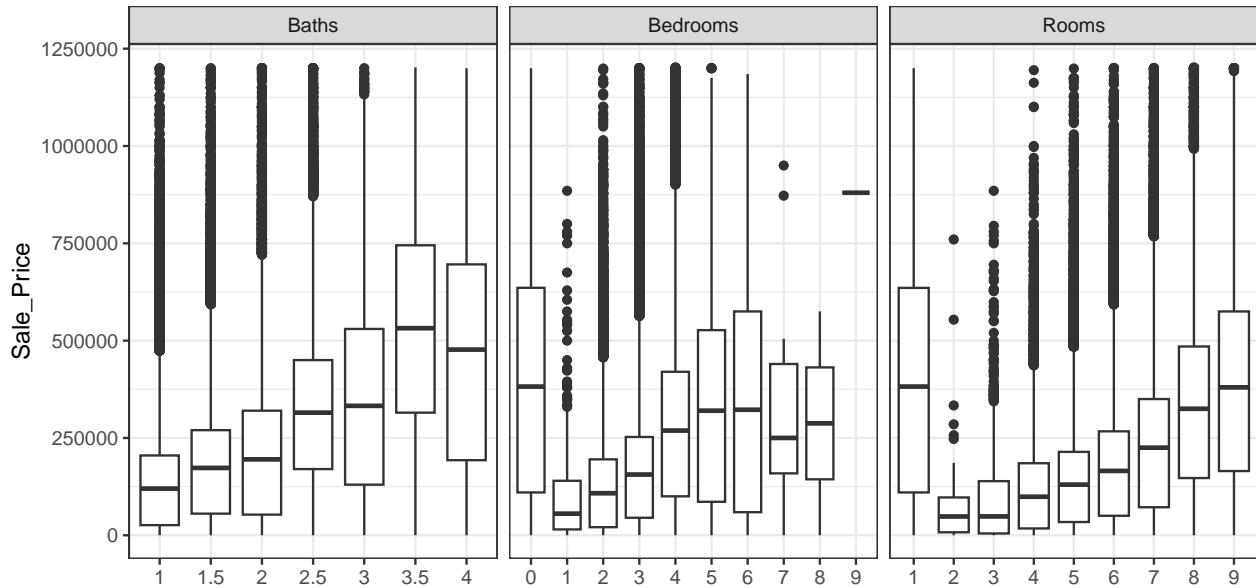


Figure 4: A series of boxplots for the variables relating to number of rooms present.

The final visualization of interest is a scatterplot of sale price against both building square footage and land square footage (Figure 5). Here, it can be seen that for listings with high building square footage, we see higher sale price. The relationship is the same for land square footage, although the highest sale prices occur at high building square footage and average land square footage.

```
data %>%
  ggplot(aes(x = `Building_Square_Feet` ,
             y = `Land_Square_Feet` ,
             color = `Sale_Price`)) +
  geom_point(size = 2) +
  labs(x = "Building Square Footage",
       y = "Land Square Footage",
       color = "Sale Price ($)")
```

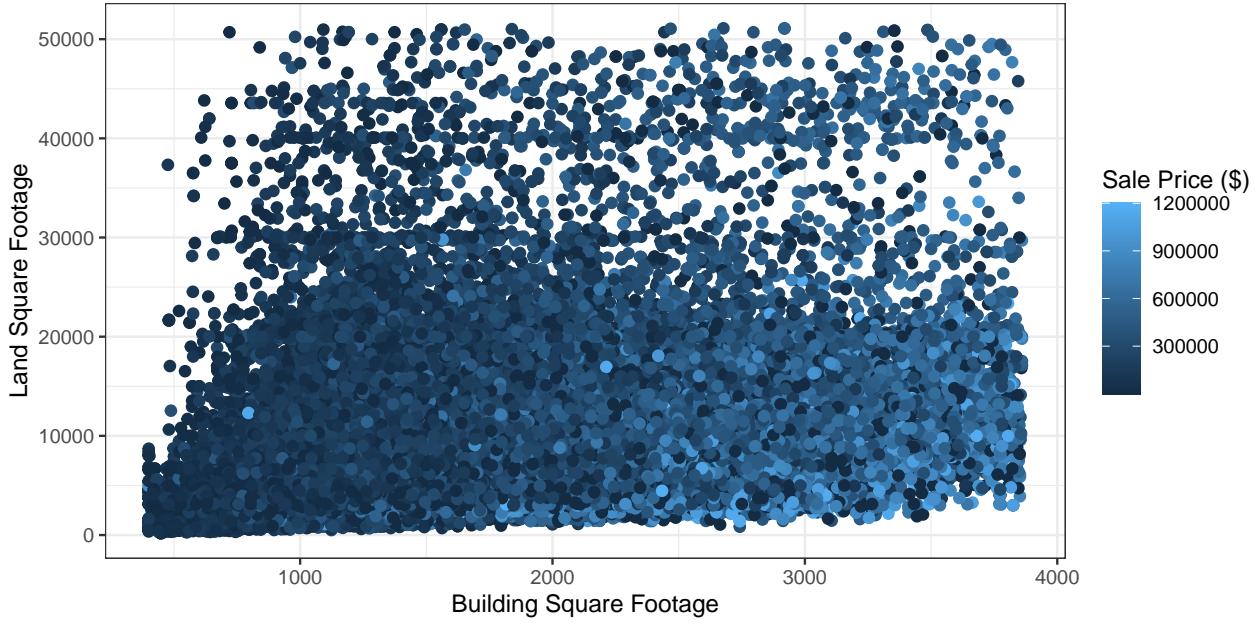


Figure 5: A scatterplot of the relationship between sale price and building/land square footage.

### 2.3 Hypothesis Development

From the exploration performed above, we hypothesize that building square footage, land square footage, the number of rooms, and location are likely going to have the highest impact on sale price.

## 3 Model Development and Performance Evaluation

Before starting the modelling process, variables were factored (if categorical) or scaled to have mean of 0 and variance 1 (if quantitative). This ensured that models had the best chance of converging. Additionally, some variables were removed due to having only 1 value or being of no importance.

```
# Scaling numeric variable
Model_Data = data %>%
  select(-c(Modeling_Group,
    Age,
    Use,
    Sale_Half_of_Year,
    `...1`,
    PIN,
    Census_Tract,
    Deed_No,
    Town_and_Neighborhood,
```

```

    Neighborhood_Code_Mapping)) %>%
mutate(Land_Square_Feet = scale(Land_Square_Feet),
       Building_Square_Feet = scale(Building_Square_Feet),
       Estimate_Land = scale(Estimate_Land),
       Estimate_Building = scale(Estimate_Building),
       Lot_Size = scale(Lot_Size)) %>%
filter(Sale_Price > 499)

```

At this point, the data were split into training and testing sets by randomly sampling 80% of the rows for the training set and leaving the remaining rows for the testing set.

```

# Sampling rows at random
ids_train = sample(1:nrow(Model_Data),
                  size = round(0.8*nrow(Model_Data)),
                  replace = FALSE)

# Splitting data
train = Model_Data[ids_train,]
test = Model_Data[-ids_train,]

```

To find the best Simple Linear Regression model, all single predictor models were searched and compared on AIC. The top-performing model involved the predictor `Estimate_Building` to predict sale price. A summary of the model fit using K-fold cross-validation is shown below. Note that the  $R^2$  indicates fairly poor model fit, but this is to be expected as it is only a single predictor.

```

# Define cross-validation method with 5 folds
train_control <- trainControl(method = "cv",
                               number = 5)

# Build model using linear model
slr <- train(Sale_Price~Estimate_Building, data = train,
              trControl = train_control,
              method = "lm")

# Summary of model
print(slr)

```

```

## Linear Regression
##
## 126664 samples
##      1 predictor
##

```

```

## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101332, 101330, 101331, 101331, 101332
## Resampling results:
##
##    RMSE      Rsquared     MAE
##    110616.8  0.6513384  71802.58
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

slr_preds = predict(slr, test)
slr_mse = Metrics::mse(slr_preds, test$Sale_Price)
print(paste("MSE from Test Set: ", slr_mse))

```

```
## [1] "MSE from Test Set: 12233023834.1165"
```

To find the best Multiple Linear Regression model, we used all available predictors with no interactions. A summary of the cross-validation process is provided. Then, we predicted to the test data and calculated the mean squared error.

```

# Train my model using k-fold cross validation
mlr <- train(Sale_Price~., data = train,
              trControl = train_control,
              method = "lm")

# Print model specifications
print(mlr)

## Linear Regression
##
## 126664 samples
##      60 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101332, 101331, 101332, 101331, 101330
## Resampling results:
##
##    RMSE      Rsquared     MAE
##    85467.95  0.7918842  58622.33
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

```

```

# Predict to test data
mlr_preds = predict(mlr, test)
mlr_mse = Metrics::mse(mlr_preds, test$Sale_Price)
print(paste("MSE from Test Set: ", mlr_mse))

## [1] "MSE from Test Set: 7472850774.75837"

```

Starting with the MLR model, subset selection was performed via backwards selection. Each iteration, the term that had the lowest impact on AIC was removed until no other terms needed to be removed. Once the ideal model formula was determined, this model was re-fit using 5-fold cross-validation. The best subset selection process resulted in a model using Lot\_Size, Building\_Square\_Feet, Beds, and Baths to predict Sale\_Price.

```

# Refit MLR model
mlr = lm(Sale_Price ~ ., data = train)

# Determine best model
best_subset <- MASS::stepAIC(mlr, direction = "backward", scope = ~ 1)

# Refit best model
best_subset <- train(Sale_Price ~ Lot_Size + Building_Square_Feet + Bedrooms + Baths,
                      data = train,
                      trControl = train_control,
                      method = 'lm')

# Print model specifications
print(best_subset)

## Linear Regression
##
## 126664 samples
##      4 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101331, 101331, 101332, 101331, 101331
## Resampling results:
##
##    RMSE     Rsquared     MAE
##    148738.4  0.3697105  109168.6
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

```

```

# Predict to test data
bs_preds = predict(best_subset, test)
bs_mse = Metrics::mse(bs_preds, test$Sale_Price)
print(paste("MSE from Test Set: ", bs_mse))

## [1] "MSE from Test Set: 22338772109.1458"

```

We fit Ridge and Lasso regression models using am mixutre of the `caret` and `glmnet` packages. `glmnet` was used to find the sequence of  $\lambda$  values to choose from, while `caret` was used to ensure consistency with how we fit our other models. Ridge and Lasso regression can be easily fit using the `glmnet` package alone.

```

library(glmnet)
data.train.mat <- model.matrix(Sale_Price ~ ., data = train)[,-1]
data.test.mat <- model.matrix(Sale_Price ~ ., data = test)[,-1]

# Fitting ridge regression model
tune.grid.ridge = expand.grid(alpha = 0,
                               lambda = glmnet(data.train.mat,
                                                train$Sale_Price,
                                                alpha = 0)$lambda)
fit.ridge <- train(Sale_Price ~ ., data = train,
                     method = 'glmnet',
                     trControl = train_control,
                     tuneGrid = tune.grid.ridge)

# Tuning Parameters
# print(fit.ridge)

# fitting the model on the test data
ridge_pred <- predict(fit.ridge, test)
ridge_mse = Metrics::mse(ridge_pred, test$Sale_Price)
print(paste("MSE from Test Set: ", ridge_mse))

## [1] "MSE from Test Set: 7541838873.52322"

```

```
# model coefficients
```

```
coef(fit.ridge$finalModel, s = fit.ridge$bestTune$lambda)
```

```

## 1432 x 1 sparse Matrix of class "dgCMatrix"
##                                     s1
## (Intercept)           -7.660737e+06
## Property_Class203     -4.540570e+03

```

## Property_Class204	-3.158354e+03
## Property_Class205	1.468352e+03
## Property_Class206	5.425138e+04
## Property_Class207	-8.768434e+03
## Property_Class208	4.534553e+04
## Property_Class209	4.415182e+04
## Property_Class278	2.090094e+04
## Neighborhood_Code11	-9.654008e+03
## Neighborhood_Code12	1.935911e+03
## Neighborhood_Code13	-1.552868e+04
## Neighborhood_Code14	-3.548789e+04
## Neighborhood_Code15	-5.701944e+03
## Neighborhood_Code18	-6.785824e+04
## Neighborhood_Code19	-5.436405e+04
## Neighborhood_Code20	8.572564e+03
## Neighborhood_Code21	5.750210e+03
## Neighborhood_Code22	1.349560e+04
## Neighborhood_Code23	-2.763531e+03
## Neighborhood_Code24	7.007425e+03
## Neighborhood_Code25	-1.202936e+04
## Neighborhood_Code26	-3.901278e+04
## Neighborhood_Code27	-4.629394e+04
## Neighborhood_Code30	1.546433e+04
## Neighborhood_Code31	-5.335595e+03
## Neighborhood_Code32	1.491133e+04
## Neighborhood_Code33	-3.070348e+03
## Neighborhood_Code34	-2.424544e+04
## Neighborhood_Code35	-2.009593e+04
## Neighborhood_Code36	-4.773934e+03
## Neighborhood_Code37	8.573209e+02
## Neighborhood_Code38	-2.517598e+04
## Neighborhood_Code39	3.330014e+04
## Neighborhood_Code40	7.865437e+02
## Neighborhood_Code41	3.865405e+03
## Neighborhood_Code42	-3.820993e+03
## Neighborhood_Code43	6.669024e+03
## Neighborhood_Code44	4.311804e+03
## Neighborhood_Code45	-1.124588e+04
## Neighborhood_Code46	-2.922473e+04
## Neighborhood_Code47	-3.887874e+04
## Neighborhood_Code48	-7.724144e+04
## Neighborhood_Code50	5.211051e+03
## Neighborhood_Code51	-1.460931e+04
## Neighborhood_Code52	-8.478859e+03
## Neighborhood_Code53	-1.739925e+04

## Neighborhood_Code54	-3.391718e+04
## Neighborhood_Code55	1.192352e+04
## Neighborhood_Code56	-2.911224e+04
## Neighborhood_Code60	1.414637e+03
## Neighborhood_Code61	-1.040459e+04
## Neighborhood_Code62	-6.384685e+03
## Neighborhood_Code63	1.440435e+04
## Neighborhood_Code64	-6.666801e+03
## Neighborhood_Code65	7.956086e+03
## Neighborhood_Code67	1.063122e+05
## Neighborhood_Code70	1.446044e+04
## Neighborhood_Code71	1.592224e+04
## Neighborhood_Code72	5.537294e+03
## Neighborhood_Code73	-6.361546e+04
## Neighborhood_Code74	7.435734e+04
## Neighborhood_Code75	-2.008954e+03
## Neighborhood_Code80	-6.807277e+03
## Neighborhood_Code81	-1.844548e+03
## Neighborhood_Code82	5.179123e+04
## Neighborhood_Code83	-9.607957e+03
## Neighborhood_Code84	-5.430486e+03
## Neighborhood_Code85	3.685350e+04
## Neighborhood_Code86	9.646113e+03
## Neighborhood_Code87	6.254944e+03
## Neighborhood_Code88	-9.047730e+03
## Neighborhood_Code90	1.099556e+04
## Neighborhood_Code91	-3.898143e+04
## Neighborhood_Code92	1.100677e+04
## Neighborhood_Code93	3.165156e+04
## Neighborhood_Code94	4.129581e+04
## Neighborhood_Code95	-2.662010e+04
## Neighborhood_Code96	-1.603407e+04
## Neighborhood_Code99	.
## Neighborhood_Code100	-5.556564e+03
## Neighborhood_Code101	-1.282794e+04
## Neighborhood_Code102	-3.697404e+04
## Neighborhood_Code103	1.382146e+04
## Neighborhood_Code104	4.970580e+03
## Neighborhood_Code109	-4.168338e+04
## Neighborhood_Code110	2.937623e+04
## Neighborhood_Code111	-5.697066e+03
## Neighborhood_Code112	-9.218953e+03
## Neighborhood_Code113	5.516449e+04
## Neighborhood_Code114	-1.363225e+04
## Neighborhood_Code115	-4.639681e+04

## Neighborhood_Code116	-2.241201e+04
## Neighborhood_Code117	4.462631e+04
## Neighborhood_Code120	2.760873e+03
## Neighborhood_Code121	-1.604042e+04
## Neighborhood_Code122	5.036487e+03
## Neighborhood_Code130	-2.504502e+03
## Neighborhood_Code131	-2.232622e+04
## Neighborhood_Code132	-7.525834e+03
## Neighborhood_Code133	-3.733366e+04
## Neighborhood_Code134	2.601587e+04
## Neighborhood_Code140	-2.278764e+04
## Neighborhood_Code141	2.006642e+04
## Neighborhood_Code142	1.350931e+04
## Neighborhood_Code143	3.808675e+04
## Neighborhood_Code145	-2.726903e+04
## Neighborhood_Code150	1.355247e+04
## Neighborhood_Code151	1.039413e+04
## Neighborhood_Code152	7.278226e+04
## Neighborhood_Code160	2.838580e+04
## Neighborhood_Code161	-1.516409e+04
## Neighborhood_Code162	-8.025866e+03
## Neighborhood_Code163	1.036023e+04
## Neighborhood_Code164	1.333938e+04
## Neighborhood_Code165	-1.142446e+04
## Neighborhood_Code166	1.027982e+05
## Neighborhood_Code170	1.756244e+04
## Neighborhood_Code171	-1.168168e+04
## Neighborhood_Code174	-3.452239e+04
## Neighborhood_Code175	2.901772e+04
## Neighborhood_Code180	-9.290434e+03
## Neighborhood_Code181	6.718255e+02
## Neighborhood_Code182	-2.214918e+04
## Neighborhood_Code183	-1.349115e+04
## Neighborhood_Code185	-3.851564e+03
## Neighborhood_Code190	-1.794493e+04
## Neighborhood_Code191	-1.508447e+03
## Neighborhood_Code192	1.876502e+04
## Neighborhood_Code193	2.339000e+04
## Neighborhood_Code194	2.680336e+04
## Neighborhood_Code200	-2.655205e+04
## Neighborhood_Code201	-1.566833e+03
## Neighborhood_Code210	-2.046586e+04
## Neighborhood_Code211	1.671189e+04
## Neighborhood_Code212	5.278492e+03
## Neighborhood_Code220	-1.083567e+04

## Neighborhood_Code221	-6.400261e+03
## Neighborhood_Code222	-1.676631e+04
## Neighborhood_Code223	-1.138323e+04
## Neighborhood_Code224	-1.413580e+04
## Neighborhood_Code226	-3.792505e+03
## Neighborhood_Code227	-1.240249e+05
## Neighborhood_Code230	-1.279052e+04
## Neighborhood_Code232	5.999150e+04
## Neighborhood_Code240	-1.521224e+04
## Neighborhood_Code241	8.472485e+03
## Neighborhood_Code250	-2.929663e+04
## Neighborhood_Code251	-2.615967e+04
## Neighborhood_Code255	2.539496e+04
## Neighborhood_Code257	-1.274841e+04
## Neighborhood_Code260	-1.951501e+04
## Neighborhood_Code262	-8.084279e+04
## Neighborhood_Code270	-6.575796e+04
## Neighborhood_Code271	3.184777e+04
## Neighborhood_Code274	1.284678e+04
## Neighborhood_Code275	-2.082710e+04
## Neighborhood_Code280	-2.872393e+04
## Neighborhood_Code281	-2.067143e+04
## Neighborhood_Code282	-1.647454e+04
## Neighborhood_Code290	-2.126516e+04
## Neighborhood_Code293	-2.457067e+04
## Neighborhood_Code300	1.169827e+04
## Neighborhood_Code310	-1.331358e+04
## Neighborhood_Code312	-7.109521e+03
## Neighborhood_Code314	-1.263351e+04
## Neighborhood_Code315	-3.049212e+04
## Neighborhood_Code316	2.822755e+02
## Neighborhood_Code320	-2.242691e+04
## Neighborhood_Code321	-1.230649e+04
## Neighborhood_Code323	-9.128897e+02
## Neighborhood_Code330	-2.417626e+04
## Neighborhood_Code340	-3.108282e+04
## Neighborhood_Code342	-3.745554e+04
## Neighborhood_Code344	-4.174998e+04
## Neighborhood_Code345	-2.685430e+04
## Neighborhood_Code350	3.292441e+04
## Neighborhood_Code360	-4.642668e+04
## Neighborhood_Code361	1.116291e+04
## Neighborhood_Code362	4.087098e+04
## Neighborhood_Code371	-8.277629e+03
## Neighborhood_Code380	3.992734e+04

## Neighborhood_Code390	2.780524e+03
## Neighborhood_Code400	-3.992746e+04
## Neighborhood_Code402	-1.111988e+04
## Neighborhood_Code410	-9.872697e+03
## Neighborhood_Code420	-2.134100e+04
## Neighborhood_Code422	4.772172e+04
## Neighborhood_Code423	3.094291e+04
## Neighborhood_Code430	-3.501130e+04
## Neighborhood_Code431	2.400526e+04
## Neighborhood_Code432	4.898318e+04
## Neighborhood_Code440	1.493343e+04
## Neighborhood_Code461	6.332476e+04
## Neighborhood_Code463	3.508023e+04
## Neighborhood_Code520	-6.535037e+04
## Neighborhood_Code560	3.890042e+04
## Neighborhood_Code580	1.051638e+05
## Neighborhood_Code600	-1.195424e+05
## Land_Square_Feet	-3.619353e+03
## Town_Code11	4.416530e+04
## Town_Code12	-5.392857e+04
## Town_Code13	-1.164188e+04
## Town_Code14	-4.526682e+04
## Town_Code15	4.342602e+03
## Town_Code16	3.019001e+03
## Town_Code17	7.763601e+04
## Town_Code18	-3.452359e+04
## Town_Code19	2.218303e+04
## Town_Code20	-3.037796e+04
## Town_Code21	2.848315e+04
## Town_Code22	7.355880e+03
## Town_Code23	5.280354e+04
## Town_Code24	1.061233e+04
## Town_Code25	3.252305e+04
## Town_Code26	6.440271e+03
## Town_Code27	1.427429e+05
## Town_Code28	-2.416399e+03
## Town_Code29	-3.812767e+03
## Town_Code30	4.911045e+03
## Town_Code31	-1.018200e+04
## Town_Code32	-4.041841e+04
## Town_Code33	1.277827e+05
## Town_Code34	1.218635e+04
## Town_Code35	-1.546155e+04
## Town_Code36	-1.778517e+04
## Town_Code37	-1.314439e+04

## Town_Code38	1.546547e+04
## Town_Code39	-1.430772e+04
## Town_Code70	-2.988870e+04
## Town_Code71	4.064887e+03
## Town_Code72	-1.689708e+04
## Town_Code73	3.522574e+04
## Town_Code74	1.048632e+05
## Town_Code75	-1.356545e+04
## Town_Code76	-5.630044e+04
## Town_Code77	5.218465e+04
## Apartments5	-1.972347e+04
## Apartments6	1.502689e+04
## Wall_Material2	-3.867455e+03
## Wall_Material3	-8.225468e+03
## Wall_Material4	8.022265e+03
## Roof_Material2	2.984707e+04
## Roof_Material3	2.222898e+04
## Roof_Material4	2.770804e+04
## Roof_Material5	1.459884e+04
## Roof_Material6	2.945930e+04
## Basement2	-1.137739e+04
## Basement3	-8.608806e+03
## Basement4	-2.171264e+04
## Basement_Finish3	-9.819789e+03
## Central_Heating1	-9.245260e+02
## Central_Heating2	2.375732e+03
## Other_Heating5	1.671600e+03
## Central_Air1	5.483607e+03
## Fireplaces1	1.231435e+04
## Fireplaces2	3.496761e+04
## Attic_Type2	9.822108e+02
## Attic_Type3	4.112001e+02
## Attic_Finish1	-4.828386e+03
## Attic_Finish3	3.035344e+03
## Design_Plan1	-4.865475e+03
## Design_Plan2	-2.087133e+03
## Cathedral_Ceiling1	1.690484e+04
## Cathedral_Ceiling2	1.439474e+04
## Construction_Quality2	-6.644544e+03
## Construction_Quality3	6.556626e+03
## Site_Desirability2	4.371101e+03
## Site_Desirability3	-2.611580e+04
## Garage_1_Size1	1.872800e+02
## Garage_1_Size2	-3.919518e+03
## Garage_1_Size3	2.730563e+02

## Garage_1_Size4	-1.263212e+03
## Garage_1_Size5	8.368469e+03
## Garage_1_Size6	1.025329e+04
## Garage_1_Size7	1.272070e+04
## Garage_1_Material1	-8.540850e+02
## Garage_1_Material2	4.830645e+02
## Garage_1_Material3	1.950977e+03
## Garage_1_Material4	2.787807e+03
## Garage_1_Attachment1	-3.347001e+03
## Garage_1_Attachment2	2.638874e+03
## Garage_1_Area1	-4.563648e+03
## Garage_1_Area2	1.679690e+03
## Garage_2_Size2	3.776756e+03
## Garage_2_Size3	-5.327998e+03
## Garage_2_Size4	4.510121e+04
## Garage_2_Size5	4.849640e+04
## Garage_2_Size7	-1.227278e+02
## Garage_2_Material1	-4.247371e+03
## Garage_2_Material2	2.781028e+04
## Garage_2_Attachment1	-4.776717e+03
## Garage_2_Attachment2	1.429506e+03
## Garage_2_Area1	-4.965649e+03
## Garage_2_Area2	1.431711e+03
## Garage_2_Area4	-1.572515e+03
## Porch2	4.278757e+03
## Porch3	1.290194e+03
## Other_Improvements1	-3.519498e+04
## Other_Improvements2	-3.513386e+03
## Other_Improvements3	-6.809545e+03
## Other_Improvements4	-1.882027e+04
## Other_Improvements5	-3.230280e+04
## Other_Improvements6	4.586440e+03
## Other_Improvements7	-3.287487e+04
## Other_Improvements8	-3.713730e+04
## Other_Improvements9	1.096204e+04
## Other_Improvements10	-7.860114e+03
## Other_Improvements11	-1.681360e+04
## Other_Improvements12	-1.654317e+04
## Other_Improvements13	-8.110200e+03
## Other_Improvements14	5.789763e+04
## Other_Improvements15	4.751812e+03
## Other_Improvements16	1.192931e+04
## Other_Improvements17	2.756650e+04
## Other_Improvements18	-7.855438e+03
## Other_Improvements19	3.440236e+04

## Other_Improvements20	-2.470450e+04
## Other_Improvements21	1.288054e+04
## Other_Improvements22	1.032787e+04
## Other_Improvements23	1.085998e+03
## Other_Improvements24	8.759361e+03
## Other_Improvements25	6.800466e+03
## Other_Improvements26	-2.652926e+04
## Other_Improvements27	-2.811906e+04
## Other_Improvements28	3.299305e+04
## Other_Improvements29	4.948248e+03
## Other_Improvements30	-8.881807e+03
## Other_Improvements31	-3.517312e+02
## Other_Improvements32	2.594710e+04
## Other_Improvements33	1.036052e+04
## Other_Improvements34	-1.854056e+04
## Other_Improvements35	-1.629534e+04
## Other_Improvements36	6.061856e+04
## Other_Improvements37	1.458358e+04
## Other_Improvements38	2.756072e+04
## Other_Improvements39	-5.289614e+04
## Other_Improvements40	4.695571e+02
## Other_Improvements41	-7.331058e+03
## Other_Improvements42	2.554138e+04
## Other_Improvements43	6.858865e+02
## Other_Improvements44	-1.785168e+04
## Other_Improvements45	1.264453e+04
## Other_Improvements46	3.136861e+03
## Other_Improvements47	2.287800e+04
## Other_Improvements48	8.870060e+03
## Other_Improvements49	-9.698474e+03
## Other_Improvements50	-1.868211e+04
## Other_Improvements51	2.835495e+04
## Other_Improvements52	-4.480526e+04
## Other_Improvements53	9.837146e+03
## Other_Improvements54	-3.380447e+04
## Other_Improvements55	-2.625661e+04
## Other_Improvements56	7.815845e+03
## Other_Improvements57	-5.642346e+03
## Other_Improvements58	3.850577e+04
## Other_Improvements59	-3.079563e+04
## Other_Improvements60	2.668870e+04
## Other_Improvements61	-3.633246e+04
## Other_Improvements62	-2.066347e+04
## Other_Improvements63	1.881222e+04
## Other_Improvements64	6.775716e+03

## Other_Improvements65	5.170130e+04
## Other_Improvements66	-1.000846e+05
## Other_Improvements67	-9.897786e+03
## Other_Improvements68	-3.360299e+04
## Other_Improvements69	-4.062912e+04
## Other_Improvements70	-1.164613e+04
## Other_Improvements71	-3.746423e+03
## Other_Improvements72	2.564855e+03
## Other_Improvements73	2.608123e+04
## Other_Improvements74	-1.434979e+04
## Other_Improvements75	-9.391588e+03
## Other_Improvements76	-9.007651e+03
## Other_Improvements77	-4.761112e+03
## Other_Improvements78	-2.034862e+04
## Other_Improvements79	-5.089692e+04
## Other_Improvements80	2.558803e+04
## Other_Improvements81	2.643399e+03
## Other_Improvements82	-2.785481e+04
## Other_Improvements83	-3.027176e+04
## Other_Improvements84	3.643670e+04
## Other_Improvements85	-1.157186e+04
## Other_Improvements86	-1.088572e+04
## Other_Improvements87	1.884412e+04
## Other_Improvements88	3.639257e+04
## Other_Improvements89	-1.575072e+04
## Other_Improvements90	2.154358e+04
## Other_Improvements91	1.152699e+04
## Other_Improvements92	9.559710e+03
## Other_Improvements93	-1.571515e+04
## Other_Improvements94	1.593630e+04
## Other_Improvements95	-3.656846e+03
## Other_Improvements96	-1.774781e+04
## Other_Improvements97	-2.986535e+03
## Other_Improvements98	9.120613e+04
## Other_Improvements99	-1.285499e+04
## Other_Improvements100	-1.029216e+04
## Other_Improvements101	3.477266e+03
## Other_Improvements102	5.135379e+03
## Other_Improvements103	-3.821731e+04
## Other_Improvements104	-1.604979e+04
## Other_Improvements105	2.839281e+04
## Other_Improvements106	-4.250814e+04
## Other_Improvements107	2.066683e+04
## Other_Improvements108	2.639341e+04
## Other_Improvements109	1.051751e+04

```

## Other_Improvements110      -2.874803e+04
## Other_Improvements111      -5.692252e+03
## Other_Improvements112      -7.767050e+03
## Other_Improvements113      9.378317e+03
## Other_Improvements114      1.958526e+03
## Other_Improvements115      9.082374e+03
## Other_Improvements116      5.929816e+03
## Other_Improvements117      -6.664290e+04
## Other_Improvements118      1.345584e+04
## Other_Improvements119      8.475381e+03
## Other_Improvements120      2.565147e+03
## Other_Improvements121      -1.621102e+02
## Other_Improvements122      1.924947e+04
## Other_Improvements123      -6.325480e+04
## Other_Improvements124      -1.084737e+05
## Other_Improvements125      -1.420230e+04
## Other_Improvements126      -2.463567e+04
## Other_Improvements127      -1.584601e+04
## Other_Improvements128      -1.276572e+04
## Other_Improvements129      1.270602e+04
## Other_Improvements130      8.334319e+03
## Other_Improvements131      -8.082089e+03
## Other_Improvements132      -1.692867e+04
## Other_Improvements133      5.693327e+04
## Other_Improvements134      5.296046e+03
## Other_Improvements135      7.610640e+03
## Other_Improvements136      2.354041e+03
## Other_Improvements137      -3.922840e+03
## Other_Improvements138      3.081878e+03
## Other_Improvements139      5.318244e+04
## Other_Improvements140      2.262059e+04
## Other_Improvements141      -2.947026e+04
## Other_Improvements142      2.270237e+04
## Other_Improvements143      1.690120e+04
## Other_Improvements144      -3.138204e+04
## Other_Improvements145      -4.187348e+03
## Other_Improvements146      -2.106674e+04
## Other_Improvements147      -2.411938e+04
## Other_Improvements148      2.046123e+04
## Other_Improvements149      -1.935389e+04
## Other_Improvements150      4.742194e+03
## Other_Improvements151      -6.435438e+04
## Other_Improvements152      1.478142e+04
## Other_Improvements153      8.492942e+03
## Other_Improvements154      2.688302e+04

```

```

## Other_Improvements155      -5.173648e+04
## Other_Improvements156      3.712231e+04
## Other_Improvements157      1.802223e+04
## Other_Improvements158      1.417789e+04
## Other_Improvements159      2.944813e+04
## Other_Improvements160      -2.187023e+04
## Other_Improvements161      -4.230785e+04
## Other_Improvements162      -2.030300e+04
## Other_Improvements163      -1.425593e+03
## Other_Improvements164      1.094877e+04
## Other_Improvements165      -1.107585e+04
## Other_Improvements166      -7.439667e+04
## Other_Improvements167      -2.459563e+04
## Other_Improvements168      6.013007e+03
## Other_Improvements169      -6.021027e+04
## Other_Improvements170      -7.300420e+04
## Other_Improvements171      -2.098766e+04
## Other_Improvements172      -2.418429e+04
## Other_Improvements173      -2.204470e+04
## Other_Improvements174      -4.859670e+04
## Other_Improvements175      -1.651991e+04
## Other_Improvements176      3.288482e+03
## Other_Improvements177      -2.849894e+04
## Other_Improvements178      7.747251e+03
## Other_Improvements179      -1.079893e+04
## Other_Improvements180      2.738591e+04
## Other_Improvements181      -3.030282e+04
## Other_Improvements182      -1.510886e+04
## Other_Improvements183      -3.804673e+04
## Other_Improvements184      2.420103e+03
## Other_Improvements185      -2.179449e+04
## Other_Improvements186      -3.841691e+04
## Other_Improvements187      3.878413e+04
## Other_Improvements188      -1.038740e+04
## Other_Improvements189      -4.817192e+04
## Other_Improvements190      7.033190e+04
## Other_Improvements191      1.213082e+04
## Other_Improvements192      -3.921791e+03
## Other_Improvements193      2.891046e+04
## Other_Improvements194      7.003636e+04
## Other_Improvements195      6.497729e+03
## Other_Improvements196      -1.897337e+04
## Other_Improvements197      -8.762376e+04
## Other_Improvements198      3.763650e+04
## Other_Improvements199      5.478935e+04

```

## Other_Improvements200	1.059541e+04
## Other_Improvements201	-3.499384e+04
## Other_Improvements202	2.216918e+04
## Other_Improvements203	-1.224739e+05
## Other_Improvements204	-2.125241e+02
## Other_Improvements205	1.012478e+04
## Other_Improvements206	-7.575328e+03
## Other_Improvements207	-1.443574e+04
## Other_Improvements208	1.739808e+04
## Other_Improvements209	-3.891422e+04
## Other_Improvements210	-3.981649e+03
## Other_Improvements211	1.280440e+03
## Other_Improvements212	2.637755e+03
## Other_Improvements213	.
## Other_Improvements214	1.350264e+04
## Other_Improvements215	-4.376379e+04
## Other_Improvements217	1.218982e+04
## Other_Improvements218	-9.072791e+04
## Other_Improvements219	-1.664666e+04
## Other_Improvements220	1.693102e+04
## Other_Improvements221	-6.641133e+03
## Other_Improvements222	4.960096e+03
## Other_Improvements223	.
## Other_Improvements224	4.437561e+04
## Other_Improvements225	-5.063976e+03
## Other_Improvements226	-4.535862e+04
## Other_Improvements227	-1.803639e+03
## Other_Improvements228	-1.093598e+04
## Other_Improvements229	.
## Other_Improvements230	2.569117e+04
## Other_Improvements231	4.897269e+03
## Other_Improvements232	1.563731e+04
## Other_Improvements233	7.364868e+04
## Other_Improvements234	8.608792e+03
## Other_Improvements235	-2.678033e+04
## Other_Improvements236	4.016318e+04
## Other_Improvements237	-5.161836e+04
## Other_Improvements238	-4.548324e+03
## Other_Improvements239	1.154847e+03
## Other_Improvements240	5.488136e+04
## Other_Improvements241	-6.604834e+04
## Other_Improvements242	1.527019e+05
## Other_Improvements243	-8.757849e+02
## Other_Improvements244	2.179631e+04
## Other_Improvements245	3.527491e+04

## Other_Improvements246	1.976899e+03
## Other_Improvements247	2.296630e+04
## Other_Improvements248	-2.340622e+04
## Other_Improvements249	4.291677e+03
## Other_Improvements250	7.349963e+03
## Other_Improvements251	7.097883e+04
## Other_Improvements252	-2.318004e+04
## Other_Improvements253	7.989514e+03
## Other_Improvements254	2.297530e+02
## Other_Improvements255	-1.158494e+04
## Other_Improvements256	6.518530e+03
## Other_Improvements257	-2.499654e+03
## Other_Improvements258	1.639095e+04
## Other_Improvements259	-4.743773e+04
## Other_Improvements260	1.048702e+05
## Other_Improvements261	-9.710573e+04
## Other_Improvements262	-1.983825e+04
## Other_Improvements264	-1.352783e+04
## Other_Improvements265	-7.189998e+04
## Other_Improvements267	-5.913763e+04
## Other_Improvements268	2.023113e+04
## Other_Improvements269	-1.410741e+04
## Other_Improvements270	-3.999411e+04
## Other_Improvements271	-5.469132e+04
## Other_Improvements272	-1.123424e+04
## Other_Improvements273	-4.959785e+04
## Other_Improvements274	4.443999e+04
## Other_Improvements275	-9.904679e+03
## Other_Improvements276	-1.546725e+04
## Other_Improvements277	-5.048458e+04
## Other_Improvements278	-5.741130e+04
## Other_Improvements279	-9.655796e+04
## Other_Improvements280	4.321340e+04
## Other_Improvements281	2.993759e+04
## Other_Improvements283	2.066219e+05
## Other_Improvements285	-3.818997e+04
## Other_Improvements286	4.518925e+04
## Other_Improvements287	-1.408770e+04
## Other_Improvements288	-3.519972e+03
## Other_Improvements289	-2.954474e+04
## Other_Improvements290	-6.659718e+03
## Other_Improvements291	2.216900e+04
## Other_Improvements292	-4.867197e+04
## Other_Improvements293	.
## Other_Improvements294	-4.761280e+04

## Other_Improvements295	9.433108e+02
## Other_Improvements296	5.187236e+04
## Other_Improvements297	-4.158690e+04
## Other_Improvements298	.
## Other_Improvements299	-9.443092e+04
## Other_Improvements300	-1.526912e+04
## Other_Improvements301	-7.574938e+04
## Other_Improvements302	-1.069538e+05
## Other_Improvements303	1.373943e+05
## Other_Improvements304	2.883854e+04
## Other_Improvements305	-6.506336e+03
## Other_Improvements306	-1.730381e+03
## Other_Improvements307	1.650595e+04
## Other_Improvements308	-1.708377e+05
## Other_Improvements309	3.420078e+04
## Other_Improvements310	-1.140844e+05
## Other_Improvements311	-9.341230e+04
## Other_Improvements312	5.474938e+04
## Other_Improvements313	.
## Other_Improvements314	.
## Other_Improvements315	3.419786e+03
## Other_Improvements316	-4.734353e+03
## Other_Improvements317	1.695902e+04
## Other_Improvements319	-6.979723e+04
## Other_Improvements320	-1.403373e+03
## Other_Improvements321	1.434869e+04
## Other_Improvements322	3.748499e+04
## Other_Improvements323	1.737089e+03
## Other_Improvements324	2.515330e+04
## Other_Improvements325	-2.172804e+04
## Other_Improvements326	-8.321704e+03
## Other_Improvements327	-1.526696e+04
## Other_Improvements328	2.095654e+04
## Other_Improvements330	-1.554689e+04
## Other_Improvements331	-6.255364e+03
## Other_Improvements332	5.574523e+03
## Other_Improvements333	9.534766e+03
## Other_Improvements335	3.275641e+04
## Other_Improvements336	-5.171084e+04
## Other_Improvements337	-2.141321e+04
## Other_Improvements338	-1.224612e+04
## Other_Improvements339	-3.520968e+03
## Other_Improvements340	5.814093e+04
## Other_Improvements341	-1.099195e+05
## Other_Improvements343	-4.594012e+04

```

## Other_Improvements344      .
## Other_Improvements345      -1.198845e+04
## Other_Improvements346      9.750003e+03
## Other_Improvements347      8.587616e+03
## Other_Improvements348      -1.065904e+05
## Other_Improvements349      2.078885e+04
## Other_Improvements350      -3.792512e+04
## Other_Improvements351      .
## Other_Improvements352      -3.344464e+04
## Other_Improvements355      .
## Other_Improvements358      2.976646e+04
## Other_Improvements359      2.452258e+04
## Other_Improvements360      -8.950573e+03
## Other_Improvements361      .
## Other_Improvements363      -2.245749e+04
## Other_Improvements364      2.471771e+02
## Other_Improvements365      -1.992905e+04
## Other_Improvements366      -3.989482e+04
## Other_Improvements367      2.748461e+04
## Other_Improvements368      -1.079035e+04
## Other_Improvements369      .
## Other_Improvements370      3.108736e+04
## Other_Improvements372      1.044557e+05
## Other_Improvements373      7.669068e+04
## Other_Improvements374      2.893637e+05
## Other_Improvements375      1.310648e+05
## Other_Improvements377      1.759321e+04
## Other_Improvements378      -2.641871e+04
## Other_Improvements380      -4.684064e+04
## Other_Improvements381      -1.334915e+04
## Other_Improvements382      -4.970649e+04
## Other_Improvements384      -8.198149e+04
## Other_Improvements385      -7.179987e+04
## Other_Improvements388      2.636080e+03
## Other_Improvements389      .
## Other_Improvements390      5.275955e+04
## Other_Improvements391      3.024186e+04
## Other_Improvements392      -1.914611e+04
## Other_Improvements394      9.826954e+04
## Other_Improvements395      1.270998e+05
## Other_Improvements396      1.627877e+04
## Other_Improvements398      -2.844332e+04
## Other_Improvements399      -7.609088e+04
## Other_Improvements400      1.836008e+03
## Other_Improvements401      3.246117e+04

```

## Other_Improvements402	3.216273e+04
## Other_Improvements403	.
## Other_Improvements404	1.275234e+05
## Other_Improvements405	3.058823e+04
## Other_Improvements406	1.000694e+04
## Other_Improvements408	1.025832e+05
## Other_Improvements409	1.493810e+04
## Other_Improvements410	-5.907793e+04
## Other_Improvements411	2.419489e+04
## Other_Improvements412	3.325878e+02
## Other_Improvements413	-1.666843e+05
## Other_Improvements415	.
## Other_Improvements416	1.940683e+03
## Other_Improvements417	6.534080e+04
## Other_Improvements418	1.744764e+04
## Other_Improvements419	9.299244e+04
## Other_Improvements420	-4.143011e+04
## Other_Improvements421	4.989267e+04
## Other_Improvements422	1.819778e+04
## Other_Improvements424	2.043415e+04
## Other_Improvements425	2.020501e+05
## Other_Improvements426	3.781040e+04
## Other_Improvements427	-3.671581e+04
## Other_Improvements428	4.492046e+04
## Other_Improvements429	4.723628e+04
## Other_Improvements430	4.876142e+04
## Other_Improvements432	1.092300e+05
## Other_Improvements433	-6.749181e+04
## Other_Improvements435	-6.105025e+04
## Other_Improvements436	.
## Other_Improvements438	3.476654e+04
## Other_Improvements439	.
## Other_Improvements440	7.643578e+04
## Other_Improvements441	4.357608e+04
## Other_Improvements442	1.913950e+04
## Other_Improvements445	-5.147328e+04
## Other_Improvements447	4.712651e+04
## Other_Improvements448	-4.195727e+04
## Other_Improvements450	-7.842293e+03
## Other_Improvements451	3.315692e+03
## Other_Improvements453	.
## Other_Improvements454	.
## Other_Improvements457	-2.860966e+04
## Other_Improvements459	-7.799356e+04
## Other_Improvements460	2.604134e+04

## Other_Improvements462	1.423973e+04
## Other_Improvements463	-1.496390e+05
## Other_Improvements464	-6.838645e+04
## Other_Improvements466	-3.849382e+04
## Other_Improvements468	-3.728817e+03
## Other_Improvements471	-1.426866e+05
## Other_Improvements473	.
## Other_Improvements475	-7.348903e+04
## Other_Improvements476	-7.959468e+03
## Other_Improvements477	.
## Other_Improvements478	2.591782e+03
## Other_Improvements480	7.573099e+04
## Other_Improvements481	-1.774940e+05
## Other_Improvements482	.
## Other_Improvements483	9.847354e+03
## Other_Improvements485	4.965010e+03
## Other_Improvements486	-1.563248e+04
## Other_Improvements489	-1.159163e+04
## Other_Improvements490	-3.095872e+04
## Other_Improvements491	.
## Other_Improvements492	-1.323034e+04
## Other_Improvements495	-2.943490e+04
## Other_Improvements496	-1.229781e+04
## Other_Improvements497	1.156937e+04
## Other_Improvements498	6.456180e+04
## Other_Improvements499	1.044302e+05
## Other_Improvements500	2.334871e+04
## Other_Improvements504	4.283626e+04
## Other_Improvements505	1.341361e+04
## Other_Improvements506	-1.333359e+04
## Other_Improvements508	.
## Other_Improvements509	4.902859e+04
## Other_Improvements512	-1.156064e+05
## Other_Improvements514	-5.719053e+04
## Other_Improvements517	-4.689380e+04
## Other_Improvements519	2.008743e+03
## Other_Improvements520	-6.408171e+04
## Other_Improvements523	-1.486874e+05
## Other_Improvements524	.
## Other_Improvements525	-6.854659e+02
## Other_Improvements527	-5.009635e+03
## Other_Improvements528	.
## Other_Improvements529	2.936172e+04
## Other_Improvements530	-1.495630e+04
## Other_Improvements531	-2.374987e+04

## Other_Improvements532	-1.014599e+03
## Other_Improvements534	-6.282761e+04
## Other_Improvements535	-1.358249e+03
## Other_Improvements536	-1.406240e+05
## Other_Improvements537	4.812583e+04
## Other_Improvements538	9.720873e+04
## Other_Improvements539	-1.710885e+04
## Other_Improvements540	.
## Other_Improvements541	2.641136e+04
## Other_Improvements542	-4.998009e+04
## Other_Improvements543	-3.110807e+03
## Other_Improvements544	-5.650395e+04
## Other_Improvements547	-4.384618e+03
## Other_Improvements549	-1.862929e+04
## Other_Improvements550	2.084533e+04
## Other_Improvements551	-9.797660e+04
## Other_Improvements552	.
## Other_Improvements554	-6.777913e+04
## Other_Improvements555	3.137710e+03
## Other_Improvements556	2.141217e+05
## Other_Improvements557	-6.158799e+04
## Other_Improvements559	4.825876e+04
## Other_Improvements560	-2.163961e+04
## Other_Improvements563	1.607173e+05
## Other_Improvements565	4.358214e+04
## Other_Improvements566	1.205337e+04
## Other_Improvements568	6.687021e+03
## Other_Improvements569	-4.693867e+04
## Other_Improvements570	1.364542e+04
## Other_Improvements571	4.617140e+04
## Other_Improvements573	8.777191e+04
## Other_Improvements574	-2.044038e+05
## Other_Improvements575	1.241557e+04
## Other_Improvements576	.
## Other_Improvements577	.
## Other_Improvements579	-4.114531e+04
## Other_Improvements581	-2.363900e+04
## Other_Improvements582	6.395374e+04
## Other_Improvements583	3.194766e+04
## Other_Improvements589	9.449614e+04
## Other_Improvements590	-6.394818e+02
## Other_Improvements592	-1.188356e+04
## Other_Improvements594	.
## Other_Improvements595	3.515110e+03
## Other_Improvements596	4.738633e+04

## Other_Improvements598	2.879081e+03
## Other_Improvements599	1.168778e+04
## Other_Improvements600	4.589267e+04
## Other_Improvements607	6.889679e+04
## Other_Improvements608	-1.059531e+05
## Other_Improvements612	.
## Other_Improvements615	1.359497e+05
## Other_Improvements616	-4.384110e+04
## Other_Improvements619	.
## Other_Improvements620	2.856815e+03
## Other_Improvements621	-4.559949e+04
## Other_Improvements624	-4.184100e+03
## Other_Improvements625	6.910836e+03
## Other_Improvements627	.
## Other_Improvements638	-5.534102e+04
## Other_Improvements639	-2.740338e+04
## Other_Improvements640	-1.788578e+04
## Other_Improvements646	.
## Other_Improvements649	1.339269e+04
## Other_Improvements650	1.834065e+03
## Other_Improvements651	7.350028e+04
## Other_Improvements652	3.363379e+04
## Other_Improvements655	-5.973672e+04
## Other_Improvements656	2.378176e+04
## Other_Improvements657	.
## Other_Improvements658	.
## Other_Improvements659	.
## Other_Improvements660	.
## Other_Improvements661	1.923402e+05
## Other_Improvements662	1.325501e+05
## Other_Improvements663	6.672924e+04
## Other_Improvements664	1.569739e+04
## Other_Improvements665	2.382610e+04
## Other_Improvements667	1.013617e+05
## Other_Improvements675	-9.921016e+04
## Other_Improvements678	7.801677e+04
## Other_Improvements681	.
## Other_Improvements687	-3.209900e+04
## Other_Improvements688	4.307034e+04
## Other_Improvements690	-3.452266e+04
## Other_Improvements693	-1.894686e+04
## Other_Improvements695	2.738074e+04
## Other_Improvements696	-2.950234e+03
## Other_Improvements700	-2.769939e+04
## Other_Improvements702	3.682943e+03

## Other_Improvements704	4.097587e+04
## Other_Improvements705	6.916951e+04
## Other_Improvements708	.
## Other_Improvements710	-2.727711e+04
## Other_Improvements712	-7.214792e+03
## Other_Improvements714	.
## Other_Improvements715	1.944894e+04
## Other_Improvements717	.
## Other_Improvements720	-1.901160e+04
## Other_Improvements721	-5.059927e+04
## Other_Improvements723	-3.691567e+04
## Other_Improvements725	6.384668e+04
## Other_Improvements726	9.755124e+03
## Other_Improvements730	-4.921266e+04
## Other_Improvements733	-1.004503e+05
## Other_Improvements740	1.497272e+04
## Other_Improvements741	.
## Other_Improvements742	1.459080e+05
## Other_Improvements748	-1.035919e+05
## Other_Improvements749	-7.827737e+04
## Other_Improvements750	.
## Other_Improvements755	-4.257637e+04
## Other_Improvements756	.
## Other_Improvements757	-3.301797e+04
## Other_Improvements760	2.971804e+04
## Other_Improvements762	.
## Other_Improvements765	5.212141e+04
## Other_Improvements766	-3.171967e+04
## Other_Improvements768	.
## Other_Improvements769	-9.956842e+04
## Other_Improvements770	4.961752e+04
## Other_Improvements772	-8.051630e+03
## Other_Improvements773	.
## Other_Improvements774	.
## Other_Improvements775	-1.222061e+05
## Other_Improvements776	3.099214e+04
## Other_Improvements777	-4.446094e+04
## Other_Improvements778	-5.330469e+04
## Other_Improvements780	1.187555e+04
## Other_Improvements785	.
## Other_Improvements787	-3.898478e+04
## Other_Improvements790	-1.803074e+04
## Other_Improvements792	-4.690594e+03
## Other_Improvements795	-5.362448e+04
## Other_Improvements798	-7.763323e+04

## Other_Improvements800	4.224523e+04
## Other_Improvements801	-3.100850e+04
## Other_Improvements802	-9.692580e+04
## Other_Improvements803	.
## Other_Improvements805	3.171822e+04
## Other_Improvements806	-2.299622e+04
## Other_Improvements808	-9.557774e+04
## Other_Improvements809	.
## Other_Improvements810	1.158749e+05
## Other_Improvements812	-4.466101e+04
## Other_Improvements815	-1.769544e+04
## Other_Improvements816	1.422778e+04
## Other_Improvements819	5.768238e+04
## Other_Improvements821	.
## Other_Improvements823	2.301302e+04
## Other_Improvements824	.
## Other_Improvements825	9.807811e+04
## Other_Improvements831	1.496796e+04
## Other_Improvements832	.
## Other_Improvements833	1.398767e+04
## Other_Improvements835	.
## Other_Improvements836	2.714732e+04
## Other_Improvements841	.
## Other_Improvements842	6.931249e+04
## Other_Improvements843	-7.072605e+04
## Other_Improvements846	-1.695630e+04
## Other_Improvements847	2.109828e+04
## Other_Improvements848	3.582805e+04
## Other_Improvements849	7.523952e+04
## Other_Improvements850	4.733644e+04
## Other_Improvements852	-2.963018e+04
## Other_Improvements853	-1.961156e+05
## Other_Improvements854	5.668744e+04
## Other_Improvements855	1.012754e+05
## Other_Improvements858	-6.158481e+04
## Other_Improvements861	.
## Other_Improvements864	-5.105756e+04
## Other_Improvements865	.
## Other_Improvements866	.
## Other_Improvements869	-1.296224e+05
## Other_Improvements872	-5.591059e+04
## Other_Improvements873	6.508021e+04
## Other_Improvements875	-4.848461e+04
## Other_Improvements876	-1.679109e+04
## Other_Improvements878	.

## Other_Improvements879	-1.607928e+05
## Other_Improvements880	-3.356858e+03
## Other_Improvements882	-8.552170e+04
## Other_Improvements884	.
## Other_Improvements890	-4.064273e+04
## Other_Improvements892	-3.377684e+04
## Other_Improvements898	.
## Other_Improvements899	-1.348339e+05
## Other_Improvements902	.
## Other_Improvements905	.
## Other_Improvements906	6.245816e+04
## Other_Improvements908	1.399050e+05
## Other_Improvements910	.
## Other_Improvements912	9.388682e+03
## Other_Improvements915	1.191786e+05
## Other_Improvements918	-7.858033e+04
## Other_Improvements934	3.741675e+04
## Other_Improvements935	7.771104e+04
## Other_Improvements940	.
## Other_Improvements943	2.830955e+04
## Other_Improvements950	-4.355237e+04
## Other_Improvements955	-4.398115e+04
## Other_Improvements956	-3.063570e+04
## Other_Improvements960	.
## Other_Improvements961	.
## Other_Improvements965	-1.499531e+05
## Other_Improvements966	4.479986e+04
## Other_Improvements975	-4.095239e+04
## Other_Improvements976	3.389279e+04
## Other_Improvements980	3.975742e+04
## Other_Improvements981	4.438108e+04
## Other_Improvements984	-4.028724e+04
## Other_Improvements985	.
## Other_Improvements994	.
## Other_Improvements995	8.830475e+04
## Other_Improvements997	-1.146378e+04
## Other_Improvements1000	-7.130158e+04
## Other_Improvements1018	-1.254598e+05
## Other_Improvements1020	.
## Other_Improvements1021	-1.146188e+05
## Other_Improvements1023	4.667290e+04
## Other_Improvements1026	2.731379e+05
## Other_Improvements1030	-8.173522e+03
## Other_Improvements1032	1.286217e+05
## Other_Improvements1045	3.107172e+04

```

## Other_Improvements1047      -9.342509e+04
## Other_Improvements1048      .
## Other_Improvements1050      1.189432e+05
## Other_Improvements1055      6.902078e+05
## Other_Improvements1057      8.248416e+04
## Other_Improvements1058      -4.891133e+04
## Other_Improvements1062      -2.501463e+04
## Other_Improvements1064      8.874663e+04
## Other_Improvements1065      9.842108e+04
## Other_Improvements1067      6.266284e+04
## Other_Improvements1069      .
## Other_Improvements1072      4.051959e+04
## Other_Improvements1076      6.142534e+04
## Other_Improvements1084      7.737292e+03
## Other_Improvements1088      -1.548663e+05
## Other_Improvements1090      .
## Other_Improvements1091      4.925251e+03
## Other_Improvements1093      -2.169631e+04
## Other_Improvements1095      -5.162027e+04
## Other_Improvements1099      .
## Other_Improvements1100      2.060932e+04
## Other_Improvements1102      8.584275e+03
## Other_Improvements1105      .
## Other_Improvements1117      -1.073231e+05
## Other_Improvements1120      -2.564170e+04
## Other_Improvements1124      2.457855e+04
## Other_Improvements1125      -2.370253e+04
## Other_Improvements1126      -9.259264e+04
## Other_Improvements1127      1.958000e+05
## Other_Improvements1128      3.427804e+04
## Other_Improvements1133      1.225620e+04
## Other_Improvements1134      .
## Other_Improvements1140      .
## Other_Improvements1146      3.537014e+04
## Other_Improvements1153      1.287263e+05
## Other_Improvements1163      -5.739142e+04
## Other_Improvements1167      .
## Other_Improvements1173      1.360160e+05
## Other_Improvements1175      -4.648641e+04
## Other_Improvements1183      .
## Other_Improvements1185      4.202464e+04
## Other_Improvements1200      4.539545e+04
## Other_Improvements1201      1.215133e+05
## Other_Improvements1202      -5.363014e+03
## Other_Improvements1203      .

```

## Other_Improvements1205	-5.366599e+04
## Other_Improvements1216	.
## Other_Improvements1217	-2.003870e+04
## Other_Improvements1226	1.378208e+05
## Other_Improvements1233	-7.017353e+03
## Other_Improvements1237	-1.041563e+05
## Other_Improvements1246	2.221274e+05
## Other_Improvements1250	-7.456511e+04
## Other_Improvements1251	1.289120e+04
## Other_Improvements1267	.
## Other_Improvements1268	.
## Other_Improvements1273	1.374277e+05
## Other_Improvements1278	7.519672e+04
## Other_Improvements1281	1.555213e+05
## Other_Improvements1282	2.787503e+04
## Other_Improvements1283	.
## Other_Improvements1285	1.706423e+04
## Other_Improvements1286	-7.683119e+04
## Other_Improvements1290	-2.288504e+04
## Other_Improvements1293	.
## Other_Improvements1300	-2.426615e+04
## Other_Improvements1308	1.405252e+05
## Other_Improvements1315	1.073631e+04
## Other_Improvements1321	.
## Other_Improvements1345	-1.846047e+04
## Other_Improvements1349	3.033949e+04
## Other_Improvements1358	3.022868e+04
## Other_Improvements1368	6.289934e+03
## Other_Improvements1370	.
## Other_Improvements1371	.
## Other_Improvements1387	.
## Other_Improvements1397	.
## Other_Improvements1400	-3.309575e+04
## Other_Improvements1401	-1.185267e+05
## Other_Improvements1410	1.586513e+04
## Other_Improvements1415	.
## Other_Improvements1430	-1.093917e+04
## Other_Improvements1432	8.252668e+04
## Other_Improvements1439	-1.320958e+04
## Other_Improvements1445	-9.288306e+04
## Other_Improvements1446	-2.305934e+04
## Other_Improvements1453	-8.746478e+04
## Other_Improvements1464	.
## Other_Improvements1476	5.531761e+04
## Other_Improvements1494	-2.293719e+04

```

## Other_Improvements1502      2.002342e+04
## Building_Square_Feet        2.373864e+04
## Repair_Condition2          -2.323673e+03
## Repair_Condition3          -1.161759e+04
## Multi_Code3                 1.774316e+03
## Multi_Code4                 1.213387e+04
## Multi_Code5                 7.715892e+04
## Number_of_Commercial_Units1 -5.164478e+04
## Number_of_Commercial_Units2 -3.522425e+04
## Number_of_Commercial_Units5 -1.812488e+04
## Estimate_Land               3.197750e+04
## Estimate_Building           4.679760e+04
## Longitude                   -7.169389e+03
## Latitude                     9.205508e+04
## Multi_Property_Indicator1   -1.620687e+05
## OHare_Noise1                1.714745e+04
## Floodplain1                 -1.663874e+04
## Road_Proximity1              -2.468247e+04
## Sale_Year                    1.597196e+03
## Sale_Quarter                  4.657742e+02
## Sale_Half_Year                8.862768e+02
## Sale_Quarter_of_Year2         8.609698e+03
## Sale_Quarter_of_Year3         8.617617e+03
## Sale_Quarter_of_Year4         -1.809693e+03
## Sale_Month_of_Year            7.859783e+02
## Most_Recent_Sale1             3.918067e+04
## Age_Decade                   -5.726366e+03
## Pure_Market_Filter1           3.134239e+04
## Garage_Indicator1             -9.451181e+02
## Lot_Size                      -3.980475e+03
## Sell_Date                     4.877861e+00
## Rooms                         9.610297e+02
## Bedrooms                      -3.058887e+03
## Baths                          1.653230e+04
## Area2                          -3.024285e+04
## Area3                          -3.844608e+04
## Area5                          1.457379e+05
## Area8                          -6.845424e+04
## Area9                          -6.469099e+04
## Area10                         2.590085e+04
## Area11                         5.705271e+04
## Area12                         7.459296e+03
## Area13                         4.483038e+04
## Area14                         1.659704e+05
## Area15                         1.248743e+03

```

## Area16	-5.491726e+04
## Area17	8.982950e+04
## Area18	2.690355e+04
## Area19	-1.252669e+04
## Area20	-3.542161e+04
## Area21	-3.045135e+04
## Area22	3.030048e+03
## Area23	-1.737739e+04
## Area24	-2.107648e+03
## Area25	-1.732992e+04
## Area26	-7.516261e+01
## Area27	-2.871185e+03
## Area28	-1.133725e+04
## Area29	-3.646278e+04
## Area30	-2.556218e+04
## Area31	-2.705419e+04
## Area32	5.821226e+01
## Area33	1.832812e+04
## Area40	1.609219e+04
## Area41	2.354120e+04
## Area42	5.674284e+04
## Area43	6.892977e+04
## Area50	1.307436e+04
## Area51	4.482285e+04
## Area52	1.039697e+05
## Area53	6.216077e+04
## Area60	-3.852622e+04
## Area61	-4.069795e+04
## Area62	-2.684363e+04
## Area63	-4.461638e+04
## Area70	-1.067061e+04
## Area71	-2.149942e+04
## Area72	-5.531315e+03
## Area73	-3.240738e+04
## Area80	-2.430528e+04
## Area81	1.253472e+04
## Area82	-5.929178e+03
## Area83	2.263623e+03
## Area90	-2.613465e+04
## Area91	-1.781238e+04
## Area92	1.830517e+04
## Area93	3.152476e+04
## Sub_Area02	-8.213140e+03
## Sub_Area03	-6.577563e+03
## Sub_Area04	-6.956449e+03

## Sub_Area05	2.726251e+03
## Sub_Area06	2.376146e+04
## Sub_Area07	2.014122e+04
## Sub_Area08	3.668188e+02
## Sub_Area09	-1.385952e+04
## Sub_Area10	-1.200597e+04
## Sub_Area11	2.046488e+03
## Sub_Area12	4.550331e+03
## Sub_Area13	5.016988e+03
## Sub_Area14	-2.458666e+03
## Sub_Area15	-5.501832e+03
## Sub_Area16	-1.448472e+04
## Sub_Area17	-8.315389e+03
## Sub_Area18	-1.927102e+03
## Sub_Area19	-1.568493e+04
## Sub_Area20	-1.384667e+04
## Sub_Area21	-1.096118e+04
## Sub_Area22	-1.123728e+04
## Sub_Area23	-6.509925e+03
## Sub_Area24	-5.664112e+03
## Sub_Area25	6.345902e+03
## Sub_Area26	9.995703e+03
## Sub_Area27	-8.624420e+03
## Sub_Area28	-1.197304e+04
## Sub_Area29	-7.779078e+03
## Sub_Area30	-9.317749e+03
## Sub_Area31	-6.075991e+01
## Sub_Area32	4.929293e+02
## Sub_Area33	-3.360417e+03
## Sub_Area34	-1.156113e+03
## Sub_Area35	1.845042e+04
## Sub_Area36	2.247480e+04
## Sub_Area41	-6.096307e+03
## Sub_Area42	9.255945e+03
## Sub_Area43	5.335318e+03
## Sub_Area44	-3.291126e+03
## Sub_Area50	1.044604e+04
## Sub_Area51	1.262102e+04
## Sub_Area52	7.467043e+03
## Sub_Area53	1.170726e+04
## Sub_Area54	1.218942e+04
## Sub_Area61	9.341359e+03
## Sub_Area62	1.170289e+04
## Sub_Area63	1.302934e+04
## Sub_Area64	2.363678e+04

## Sub_Area71	8.704009e+03
## Sub_Area72	1.058098e+03
## Sub_Area73	1.431102e+04
## Sub_Area74	2.751607e+04
## Sub_Area81	4.781343e+03
## Sub_Area82	1.002784e+04
## Sub_Area83	-4.543383e+02
## Sub_Area84	7.317495e+03
## Sub_Area90	1.215335e+04
## Sub_Area91	2.657986e+03
## Sub_Area92	7.850613e+03
## Sub_Area93	1.850577e+04
## Sub_Area94	1.405757e+04
## Block01	3.113644e+03
## Block02	-3.872536e+03
## Block03	-3.952303e+03
## Block04	-2.019962e+03
## Block05	3.095712e+03
## Block06	-4.963648e+03
## Block07	-1.894567e+03
## Block08	-1.276586e+03
## Block09	-4.414726e+03
## Block10	-2.076619e+03
## Block11	-3.209250e+03
## Block12	3.186419e+03
## Block13	3.824674e+03
## Block14	-3.748077e+03
## Block15	-1.341656e+03
## Block16	6.849258e+03
## Block17	1.075009e+03
## Block18	8.351930e+03
## Block19	4.424396e+03
## Block20	1.713469e+03
## Block21	2.765601e+03
## Block22	1.716985e+03
## Block23	-2.279970e+03
## Block24	1.680502e+04
## Block25	2.221550e+04
## Block26	1.753307e+04
## Block27	5.622925e+01
## Block28	1.589499e+04
## Block29	-6.963923e+03
## Block30	1.673888e+03
## Block31	3.358990e+02
## Block32	5.834059e+02

## Block33	2.122053e+02
## Block34	-5.837285e+03
## Block35	1.075257e+04
## Block36	7.260703e+03
## Block37	8.083339e+04
## Block38	6.415385e+04
## Block39	1.519249e+04
## Block40	1.973583e+03
## Block41	1.138004e+03
## Block42	-9.987228e+02
## Block43	-7.379241e+02
## Block44	1.451690e+04
## Block45	3.172694e+04
## Block46	3.065626e+04
## Block62	-6.926978e+04
## Block63	4.982519e+04
## Block64	5.826687e+04
## Block71	-6.318109e+04
## Block73	-5.448726e+03
## Block84	1.251738e+04
## Block91	2.621281e+04
## Parcel01	9.936613e+02
## Parcel02	1.395451e+03
## Parcel03	1.770779e+03
## Parcel04	-2.598834e+03
## Parcel05	-3.020514e+03
## Parcel06	-3.446287e+03
## Parcel07	-1.307771e+03
## Parcel08	1.100357e+04
## Parcel09	-4.415446e+03
## Parcel10	-2.262970e+03
## Parcel11	-6.353928e+03
## Parcel12	4.513999e+04
## Parcel13	1.580183e+04
## Parcel14	-1.803947e+04
## Parcel15	-2.225270e+04
## Parcel16	4.602023e+04
## Parcel17	-6.415152e+04
## Parcel18	-3.029043e+04
## Parcel19	-4.873615e+04
## Parcel20	-2.333376e+03
## Parcel21	-1.515763e+04
## Parcel22	2.905202e+03
## Parcel23	-7.293066e+04
## Parcel24	1.398125e+04

## Parcel25	-1.311208e+04
## Parcel26	6.032595e+04
## Parcel27	-9.934244e+04
## Parcel28	-1.338881e+05
## Parcel30	-2.174639e+03
## Parcel31	-1.159819e+04
## Parcel32	-3.949010e+04
## Parcel40	-1.718602e+03
## Parcel41	-2.823646e+03
## Parcel42	-5.869608e+04
## Parcel50	-2.284792e+03
## Parcel51	-1.671783e+04
## Parcel52	-4.261187e+04
## Parcel60	8.463397e+01
## Parcel61	-8.270298e+03
## Parcel62	-9.503967e+03
## Parcel70	-1.115094e+03
## Parcel71	-2.214838e+04
## Parcel72	-1.315069e+05
## Parcel80	-4.666496e+02
## Parcel81	1.973533e+03
## Parcel90	-2.746620e+03
## Parcel91	-1.206068e+04
## Multicode0100	6.352658e+02
## Multicode0200	-1.039510e+03
## Multicode0300	1.922878e+03
## Multicode0400	9.369834e+02
## Multicode0500	2.541523e+03
## Multicode0600	1.531165e+03
## Multicode0700	2.922328e+02
## Multicode0800	5.008340e+02
## Multicode0900	4.061055e+02
## Multicode1000	3.691053e+02
## Multicode1100	1.219418e+03
## Multicode1200	2.951205e+03
## Multicode1300	2.167289e+03
## Multicode1400	-7.054602e+02
## Multicode1500	-1.128911e+03
## Multicode1600	-8.982279e+02
## Multicode1700	1.633950e+03
## Multicode1800	-4.722789e+02
## Multicode1900	2.195965e+03
## Multicode1e+1	-1.317369e+04
## Multicode2000	1.237073e+03
## Multicode2100	6.946432e+02

## Multicode2200	-1.783151e+03
## Multicode2300	2.006827e+01
## Multicode2400	2.235219e+03
## Multicode2500	-1.244406e+00
## Multicode2600	2.042470e+03
## Multicode2700	-3.174247e+02
## Multicode2800	-4.091453e+02
## Multicode2900	-2.978968e+03
## Multicode2e+1	.
## Multicode3000	6.430214e+02
## Multicode3100	-8.074114e+02
## Multicode3200	-4.955477e+02
## Multicode3300	-3.230503e+03
## Multicode3400	-3.135458e+03
## Multicode3500	-4.488930e+03
## Multicode3600	-5.829945e+03
## Multicode3700	-5.419656e+03
## Multicode3800	-3.224377e+03
## Multicode3900	-3.039543e+03
## Multicode4000	3.967846e+01
## Multicode4100	-7.376955e+03
## Multicode4200	-5.125310e+03
## Multicode4300	-2.115126e+03
## Multicode4400	-4.622526e+03
## Multicode4500	-4.442443e+03
## Multicode4600	-8.911740e+03
## Multicode4700	-3.937675e+03
## Multicode4800	-2.739384e+03
## Multicode4900	-1.997799e+03
## Multicode5000	2.379859e+03
## Multicode5100	-3.849490e+03
## Multicode5200	-3.118772e+03
## Multicode5300	-4.202061e+03
## Multicode5400	-1.112752e+03
## Multicode5500	-6.861739e+02
## Multicode5600	-6.176135e+03
## Multicode5700	-6.184655e+03
## Multicode5800	-6.914524e+03
## Multicode5900	-3.904773e+02
## Multicode6000	2.090829e+03
## Multicode6100	-6.930392e+03
## Multicode6200	-7.185240e+03
## Multicode6300	-8.920328e+03
## Multicode6400	-8.467834e+03
## Multicode6500	-4.938982e+03

```

## Multicode6600           4.825216e+03
## Multicode6700           5.762403e+03
## Multicode6800          -1.357032e+04
## Multicode6900          -7.535705e+03
## Multicode7000           3.605412e+03
## Multicode7100          -1.278143e+04
## Multicode7200          -2.015148e+03
## Multicode7300          -9.084396e+02
## Multicode7400           3.273140e+03
## Multicode7500          -1.449253e+04
## Multicode7600          -4.071294e+03
## Multicode7700          -5.560624e+03
## Multicode7800          -2.047662e+04
## Multicode7900          -1.157143e+04
## Multicode8000           4.538897e+02
## Multicode8100           1.463895e+02
## Multicode8200          -1.753421e+04
## Multicode8300          -2.546661e+04
## Multicode8400          -1.228498e+04
## Multicode8500          -1.837262e+04
## Multicode8600          -2.417299e+04
## Multicode8700          -3.657355e+03
## Multicode8800          -1.314390e+04
## Multicode8900          -5.787616e+03
## Multicode9000           1.269774e+03
## Multicode9100          -8.251444e+03
## Multicode9200          -1.695448e+04
## Multicode9300           2.953315e+03
## Multicode9400          -3.780742e+04
## Multicode9500          -3.709906e+04
## Multicode9600          -7.278316e+03
## Multicode9700          -1.227990e+04
## Multicode9800          -4.337193e+03
## Multicode9900          -1.354142e+04
## Multicodeee+12          2.470156e+04

```

```

# Fitting Lasso regression model
tune.grid.lasso = expand.grid(alpha = 1,
                               lambda = glmnet(data.train.mat,
                                                train$Sale_Price,
                                                alpha = 1)$lambda)
fit.lasso <- train(Sale_Price ~ ., data = train,
                     method = 'glmnet',
                     trControl = train_control,
                     tuneGrid = tune.grid.lasso)

```

```

# Tuning Parameters
print(fit.lasso)

## glmnet
##
## 126664 samples
##      60 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101330, 101331, 101332, 101331, 101332
## Resampling results across tuning parameters:
##
##     lambda      RMSE    Rsquared     MAE
##     16.59414   85497.77  0.7918009  58582.70
##     18.21205   85496.76  0.7918056  58579.89
##     19.98770   85495.96  0.7918094  58576.76
##     21.93647   85494.65  0.7918156  58573.35
##     24.07525   85492.57  0.7918254  58568.26
##     26.42256   85490.52  0.7918350  58562.02
##     28.99873   85487.40  0.7918495  58554.87
##     31.82607   85484.10  0.7918651  58546.88
##     34.92907   85480.64  0.7918814  58538.31
##     38.33461   85477.26  0.7918972  58529.27
##     42.07219   85473.60  0.7919145  58519.64
##     46.17417   85469.52  0.7919338  58508.86
##     50.67610   85465.18  0.7919542  58498.29
##     55.61695   85462.62  0.7919660  58486.69
##     61.03954   85459.39  0.7919812  58473.17
##     66.99082   85455.96  0.7919975  58459.66
##     73.52234   85454.23  0.7920054  58445.95
##     80.69068   85453.37  0.7920094  58430.96
##     88.55792   85449.98  0.7920259  58416.64
##     97.19221   85450.82  0.7920217  58399.78
##    106.66833   85449.59  0.7920280  58384.28
##    117.06836   85452.05  0.7920162  58366.35
##    128.48238   85453.16  0.7920116  58349.61
##    141.00925   85457.82  0.7919897  58330.86
##    154.75748   85462.47  0.7919687  58313.06
##    169.84614   85471.83  0.7919249  58296.08
##    186.40593   85484.52  0.7918656  58279.67
##    204.58028   85500.06  0.7917932  58264.74
##    224.52660   85521.70  0.7916915  58252.24
##    246.41767   85548.32  0.7915666  58241.34

```

##	270.44309	85579.14	0.7914220	58231.36
##	296.81096	85615.69	0.7912504	58224.51
##	325.74966	85658.05	0.7910518	58221.66
##	357.50985	85705.88	0.7908274	58221.05
##	392.36662	85760.84	0.7905697	58224.39
##	430.62188	85826.67	0.7902608	58234.21
##	472.60698	85904.16	0.7898950	58251.45
##	518.68557	85994.86	0.7894663	58274.96
##	569.25678	86102.69	0.7889547	58307.03
##	624.75861	86224.98	0.7883731	58346.05
##	685.67180	86362.37	0.7877188	58393.19
##	752.52396	86514.46	0.7869934	58443.91
##	825.89412	86687.88	0.7861630	58503.53
##	906.41777	86886.97	0.7852073	58575.95
##	994.79239	87102.52	0.7841697	58657.57
##	1091.78342	87341.38	0.7830151	58753.15
##	1198.23095	87568.38	0.7819236	58835.35
##	1315.05699	87815.47	0.7807345	58925.02
##	1443.27342	88096.53	0.7793738	59033.86
##	1583.99080	88406.82	0.7778676	59159.11
##	1738.42795	88749.68	0.7761931	59300.77
##	1907.92252	89121.31	0.7743724	59460.73
##	2093.94262	89534.15	0.7723353	59644.61
##	2298.09944	89971.11	0.7701711	59847.58
##	2522.16129	90414.29	0.7679715	60047.41
##	2768.06891	90859.57	0.7657665	60257.12
##	3037.95221	91242.22	0.7638989	60426.19
##	3334.14880	91641.70	0.7619571	60613.59
##	3659.22419	92081.09	0.7598076	60823.61
##	4015.99403	92566.14	0.7574253	61068.65
##	4407.54849	93089.00	0.7548424	61334.62
##	4837.27903	93631.26	0.7521683	61623.08
##	5308.90776	94211.24	0.7492963	61951.97
##	5826.51971	94878.65	0.7459415	62356.87
##	6394.59819	95545.12	0.7426040	62773.01
##	7018.06362	96135.17	0.7397399	63166.26
##	7702.31616	96756.42	0.7367252	63587.19
##	8453.28248	97408.72	0.7335899	64035.59
##	9277.46708	98016.81	0.7307656	64480.73
##	10182.00867	98600.27	0.7281812	64920.36
##	11174.74195	99215.93	0.7255211	65414.59
##	12264.26549	99947.85	0.7222550	66002.67
##	13460.01624	100657.67	0.7192879	66557.66
##	14772.35120	101387.27	0.7163553	67141.70
##	16212.63721	102201.62	0.7130999	67798.19

```

##   17793.34932 103174.12 0.7090571 68576.70
##   19528.17892 104222.23 0.7047175 69439.41
##   21432.15225 105248.32 0.7008782 70370.70
##   23521.76064 106163.54 0.6982724 71122.20
##   25815.10326 107194.28 0.6954305 71966.98
##   28332.04396 108357.39 0.6923232 72935.46
##   31094.38327 109480.73 0.6904171 73852.65
##   34126.04726 110754.88 0.6884748 74920.63
##   37453.29473 112111.76 0.6873054 76135.16
##   41104.94474 113671.18 0.6862483 77547.04
##   45112.62610 115519.76 0.6848414 79203.83
##   49511.05146 117709.65 0.6829112 81143.98
##   54338.31785 120294.50 0.6802337 83412.13
##   59636.23676 123336.08 0.6764422 86052.34
##   65450.69622 126902.93 0.6709402 89119.54
##   71832.05831 131069.11 0.6627341 92654.88
##   78835.59531 135825.75 0.6515173 96653.77
##   86521.96853 140433.36 0.6514051 100578.72
##   94957.75365 145782.28 0.6514051 105069.48
##   104216.01741 151975.33 0.6514051 110191.47
##   114376.95045 159115.17 0.6514051 116006.35
##   125528.56192 167311.08 0.6514051 122595.47
##   137767.44174 176679.02 0.6514051 130036.41
##   151199.59724 187251.31 0.6499115 138344.07
##
## Tuning parameter 'alpha' was held constant at a value of 1
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 1 and lambda = 106.6683.

```

```

# Fitting the model on our test data
lasso_pred <- predict(fit.lasso, test)
lasso_mse = Metrics::mse(lasso_pred, test$Sale_Price)
print(paste("MSE from Test Set: ", lasso_mse))

```

```

## [1] "MSE from Test Set: 7458837515.98409"

```

```

# model coefficients
# coef(fit.lasso$finalModel, s = fit.lasso$bestTune$lambda)

```

For the model using principle components, we first selected all numeric variables except for the response and calculated the principle components. The cumulative variance is shown below, indicating that only the first two principle components are needed.

```

# Calculating principle components using numeric data
numeric_data = Model_Data %>% select_if(is.numeric) %>% select(-Sale_Price)
PCs = prcomp(numeric_data)

# Determining how many PCs to use
PCs$sdev^2/sum(PCs$sdev^2)

## [1] 7.599511e-01 9.662336e-02 7.520483e-02 3.207665e-02 1.571743e-02
## [6] 1.045565e-02 3.960374e-03 2.199857e-03 1.770254e-03 1.281368e-03
## [11] 3.996414e-04 2.743077e-04 4.706330e-05 3.811454e-05 1.099480e-28

```

Then, a data frame is created using the first two principle components' variable values. The observed response values were then binded to this data frame and the train-test splits were made again using the original training IDs. The model was trained on the training data using the 5-fold cross-validation and predictions were made on the test set.

```

# Obtain first principle component as data
PC_data = data.frame(PCs$x[,1:2])

# Convert into data frame, adding response
PC_data = bind_cols(PC_data, data.frame(Sale_Price = Model_Data$Sale_Price))

# Split into test and train
PC_train = PC_data[ids_train,]
PC_test = PC_data[-ids_train,]

# train model with k-fold cv
pc_slr <- train(Sale_Price~., data = PC_train,
                  trControl = train_control,
                  method = "lm")

# display model
print(pc_slr)

## Linear Regression
##
## 126664 samples
##      2 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101331, 101331, 101331, 101333, 101330
## Resampling results:
##
```

```

##   RMSE      Rsquared      MAE
## 186406.6  0.01005841 137154.9
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

# predict to test data
pc_slr_preds = predict(pc_slr, PC_test)
pc_mse = Metrics::mse(pc_slr_preds, PC_test$Sale_Price)
print(paste("MSE from Test Set: ", pc_mse))

## [1] "MSE from Test Set: 35259839965.94"

# Loadings from first PC
PCs$rotation[,1]

##           Land_Square_Feet Building_Square_Feet      Estimate_Land
## 0.0008882040          0.0010883960 0.0066974675
## Estimate_Building       Longitude            Latitude
## 0.0010046124          0.0002311904 -0.0005799016
## Sale_Year                Sale_Quarter        Sale_Half_Year
## 0.2162570564          0.8730671078  0.4360019681
## Sale_Month_of_Year       Age_Decade          Lot_Size
## 0.0232759222          0.0171276107  0.0008882040
##          Rooms            Bedrooms            Baths
## 0.0016421643          0.0012608425  0.0007531130

```

A similar process was performed for the non-linear model as for the principle component model. We start by calculating the orthogonal 4<sup>th</sup> degree polynomial variables from the Estimate\_Building variable, renaming each term as Poly\_#. This data set was binded with the original data as to have all polynomial variables and the response in a single data frame. Then, train and test splits were made. The model was trained on the training set and predicted to the testing set, resulting in the MSE provided.

```

# Adding polynomial terms for later use
poly_predictors = data.frame(poly(Model_Data$Estimate_Building, 4))

Polynomial_Data = poly_predictors %>%
  rename(Poly_1 = X1,
         Poly_2 = X2,
         Poly_3 = X3,
         Poly_4 = X4) %>%
  bind_cols(Model_Data)

# Split polynomial data

```

```

poly_train = Polynomial_Data[ids_train,]
poly_test = Polynomial_Data[-ids_train,]

# Training 5th degree polynomial
poly_slr = train(Sale_Price ~ Poly_1 + Poly_2 + Poly_3 + Poly_4,
                  data = poly_train,
                  trControl = train_control,
                  method = 'lm')

```

```

# Summary of model
print(poly_slr)

```

```

## Linear Regression
##
## 126664 samples
##      4 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 101332, 101330, 101331, 101332, 101331
## Resampling results:
##
##     RMSE      Rsquared      MAE
##     108246.6  0.6661593  73244.79
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

```

```

# Predicting and Calculating MSE
poly_slr_preds = predict(poly_slr, poly_test, type = 'raw')
poly_mse = Metrics::mse(poly_slr_preds, poly_test$Sale_Price)
print(paste("MSE from Test Set: ", poly_mse))

```

```

## [1] "MSE from Test Set: 11742883379.0502"

```

Comparing the models on mean squared error when predicting to the test set, we can see which model performed the best when predicting to the test data (Table 1). From this table, the top performing model on test data was the Lasso regularized model, followed closely by the MLR model. This is likely due to overfitting from the MLR model and effective variable selection for the Lasso model.

```

tibble(Model = c("SLR", "MLR", "Backward Selection",
               "Ridge", "Lasso", "PCA", "Polynomial"),
       MSE = c(slr_mse, mlr_mse, bs_mse, ridge_mse, lasso_mse, pc_mse, poly_mse)) %>%

```

Table 1: A table of MSE for the models compared when predicting to the test data.

Model	MSE
Lasso	7458837516
MLR	7472850775
Ridge	7541838874
Polynomial	11742883379
SLR	12233023834
Backward Selection	22338772109
PCA	35259839966

```
arrange(MSE) %>%
knitr::kable(caption = "A table of MSE for the models compared when predicting to th")
```