

MTH404 R Project

Mustafif Khan

Loading Required Packages

Before the dataset can be analyzed, the following packages must be imported:

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.1      v readr      2.1.4
## v forcats    1.0.0      v stringr   1.5.0
## v ggplot2     3.4.2      v tibble    3.2.1
## v lubridate  1.9.2      v tidyr     1.3.0
## v purrr      1.0.1
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(ggplot2)
```

```
library(lubridate)
```

```
library(gridExtra)
```

```
##
```

```
## Attaching package: 'gridExtra'
```

```
##
```

```
## The following object is masked from 'package:dplyr':
```

```
##
```

```
##      combine
```

```
library(caTools)
```

```
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
```

```
##   method from
```

```
##   +.gg      ggplot2
```

```
library(dplyr)
```

Reading the Training and Test Data

From the kaggle competition, we are provided the CSV data for training and testing, and the dataset is imported like the following:

```
train_data <- read.csv("train.csv")
test_data <- read.csv("test.csv")
```

With the data, we can check if we are missing values, let's first check our training data:

```
# get the missing training values
missing_training_values <- sapply(train_data, function(x) sum(is.na(x)))
# create a data frame with column names and missing values
mtv_df <- data.frame(column = names(missing_training_values),
                     missing_values = missing_training_values)
mtv_df
```

```
##           column missing_values
## Id           Id              0
## MSSubClass    MSSubClass      0
## MSZoning      MSZoning        0
## LotFrontage   LotFrontage    259
## LotArea       LotArea         0
## Street        Street         0
## Alley         Alley        1369
## LotShape      LotShape        0
## LandContour   LandContour     0
## Utilities     Utilities       0
## LotConfig     LotConfig       0
## LandSlope     LandSlope       0
## Neighborhood  Neighborhood    0
## Condition1    Condition1      0
## Condition2    Condition2      0
## BldgType      BldgType        0
## HouseStyle    HouseStyle      0
## OverallQual   OverallQual     0
## OverallCond   OverallCond     0
## YearBuilt     YearBuilt       0
## YearRemodAdd  YearRemodAdd     0
## RoofStyle     RoofStyle       0
## RoofMatl      RoofMatl        0
## Exterior1st   Exterior1st     0
## Exterior2nd   Exterior2nd     0
## MasVnrType    MasVnrType      8
## MasVnrArea    MasVnrArea      8
## ExterQual     ExterQual       0
## ExterCond     ExterCond       0
## Foundation    Foundation      0
## BsmtQual      BsmtQual        37
## BsmtCond      BsmtCond        37
## BsmtExposure  BsmtExposure    38
## BsmtFinType1  BsmtFinType1    37
## BsmtFinSF1    BsmtFinSF1      0
## BsmtFinType2  BsmtFinType2    38
## BsmtFinSF2    BsmtFinSF2      0
## BsmtUnfSF     BsmtUnfSF       0
## TotalBsmtSF   TotalBsmtSF     0
## Heating       Heating         0
## HeatingQC     HeatingQC       0
## CentralAir    CentralAir      0
```

## Electrical	Electrical	1
## X1stFlrSF	X1stFlrSF	0
## X2ndFlrSF	X2ndFlrSF	0
## LowQualFinSF	LowQualFinSF	0
## GrLivArea	GrLivArea	0
## BsmtFullBath	BsmtFullBath	0
## BsmtHalfBath	BsmtHalfBath	0
## FullBath	FullBath	0
## HalfBath	HalfBath	0
## BedroomAbvGr	BedroomAbvGr	0
## KitchenAbvGr	KitchenAbvGr	0
## KitchenQual	KitchenQual	0
## TotRmsAbvGrd	TotRmsAbvGrd	0
## Functional	Functional	0
## Fireplaces	Fireplaces	0
## FireplaceQu	FireplaceQu	690
## GarageType	GarageType	81
## GarageYrBlt	GarageYrBlt	81
## GarageFinish	GarageFinish	81
## GarageCars	GarageCars	0
## GarageArea	GarageArea	0
## GarageQual	GarageQual	81
## GarageCond	GarageCond	81
## PavedDrive	PavedDrive	0
## WoodDeckSF	WoodDeckSF	0
## OpenPorchSF	OpenPorchSF	0
## EnclosedPorch	EnclosedPorch	0
## X3SsnPorch	X3SsnPorch	0
## ScreenPorch	ScreenPorch	0
## PoolArea	PoolArea	0
## PoolQC	PoolQC	1453
## Fence	Fence	1179
## MiscFeature	MiscFeature	1406
## MiscVal	MiscVal	0
## MoSold	MoSold	0
## YrSold	YrSold	0
## SaleType	SaleType	0
## SaleCondition	SaleCondition	0
## SalePrice	SalePrice	0

As you can notice there are data in this dataset that contains large amounts of missing values, such as columns like PoolQC, Fence, etc. We will be removing the columns with missing values like the following:

```
train_data <- select(train_data, -c(LotFrontage, Alley, MasVnrType, MasVnrArea, BsmtQual ,
                                   BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2,
                                   FireplaceQu, GarageType, GarageYrBlt, GarageFinish,
                                   GarageQual, GarageCond, PoolQC, Fence , MiscFeature ))
```

Now it would be good to also check our training data for missing values it may contain:

```
# get the missing values for the testing dataset
missing_testing_values <- sapply(test_data, function (x) sum(is.na(x)))
# create a data frame of the missing testing values
mtestv_df <- data.frame(column = names(missing_testing_values),
                        missing_values = missing_testing_values)
mtestv_df
```

##	column	missing_values
## Id	Id	0
## MSSubClass	MSSubClass	0
## MSZoning	MSZoning	4
## LotFrontage	LotFrontage	227
## LotArea	LotArea	0
## Street	Street	0
## Alley	Alley	1352
## LotShape	LotShape	0
## LandContour	LandContour	0
## Utilities	Utilities	2
## LotConfig	LotConfig	0
## LandSlope	LandSlope	0
## Neighborhood	Neighborhood	0
## Condition1	Condition1	0
## Condition2	Condition2	0
## BldgType	BldgType	0
## HouseStyle	HouseStyle	0
## OverallQual	OverallQual	0
## OverallCond	OverallCond	0
## YearBuilt	YearBuilt	0
## YearRemodAdd	YearRemodAdd	0
## RoofStyle	RoofStyle	0
## RoofMatl	RoofMatl	0
## Exterior1st	Exterior1st	1
## Exterior2nd	Exterior2nd	1
## MasVnrType	MasVnrType	16
## MasVnrArea	MasVnrArea	15
## ExterQual	ExterQual	0
## ExterCond	ExterCond	0
## Foundation	Foundation	0
## BsmtQual	BsmtQual	44
## BsmtCond	BsmtCond	45
## BsmtExposure	BsmtExposure	44
## BsmtFinType1	BsmtFinType1	42
## BsmtFinSF1	BsmtFinSF1	1
## BsmtFinType2	BsmtFinType2	42
## BsmtFinSF2	BsmtFinSF2	1
## BsmtUnfSF	BsmtUnfSF	1
## TotalBsmtSF	TotalBsmtSF	1
## Heating	Heating	0
## HeatingQC	HeatingQC	0
## CentralAir	CentralAir	0
## Electrical	Electrical	0
## X1stFlrSF	X1stFlrSF	0
## X2ndFlrSF	X2ndFlrSF	0
## LowQualFinSF	LowQualFinSF	0
## GrLivArea	GrLivArea	0
## BsmtFullBath	BsmtFullBath	2
## BsmtHalfBath	BsmtHalfBath	2
## FullBath	FullBath	0
## HalfBath	HalfBath	0

## BedroomAbvGr	BedroomAbvGr	0
## KitchenAbvGr	KitchenAbvGr	0
## KitchenQual	KitchenQual	1
## TotRmsAbvGrd	TotRmsAbvGrd	0
## Functional	Functional	2
## Fireplaces	Fireplaces	0
## FireplaceQu	FireplaceQu	730
## GarageType	GarageType	76
## GarageYrBlt	GarageYrBlt	78
## GarageFinish	GarageFinish	78
## GarageCars	GarageCars	1
## GarageArea	GarageArea	1
## GarageQual	GarageQual	78
## GarageCond	GarageCond	78
## PavedDrive	PavedDrive	0
## WoodDeckSF	WoodDeckSF	0
## OpenPorchSF	OpenPorchSF	0
## EnclosedPorch	EnclosedPorch	0
## X3SsnPorch	X3SsnPorch	0
## ScreenPorch	ScreenPorch	0
## PoolArea	PoolArea	0
## PoolQC	PoolQC	1456
## Fence	Fence	1169
## MiscFeature	MiscFeature	1408
## MiscVal	MiscVal	0
## MoSold	MoSold	0
## YrSold	YrSold	0
## SaleType	SaleType	1
## SaleCondition	SaleCondition	0

As you can see in our testing dataset we can notice columns that have high amount of missing values such as columns like `LotFrontage`, `Alley`, etc. As before we will be removing the columns with missing values like the following:

```
test_data <- select(test_data, -c(LotFrontage, Alley, MasVnrType, MasVnrArea, BsmtQual,
                                   BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2,
                                   FireplaceQu, GarageType, GarageYrBlt, GarageFinish,
                                   GarageQual, GarageCond, PoolQC, Fence, MiscFeature))
```

Analysis of the Train Data

Before we create a model to analyze our training data, we will need to look at the structure of our different columns using the `str()` function:

```
str(train_data)

## 'data.frame':   1460 obs. of  63 variables:
##  $ Id          : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ MSSubClass  : int  60 20 60 70 60 50 20 60 50 190 ...
##  $ MSZoning    : chr  "RL" "RL" "RL" "RL" ...
##  $ LotArea     : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...
##  $ Street      : chr  "Pave" "Pave" "Pave" "Pave" ...
##  $ LotShape    : chr  "Reg" "Reg" "IR1" "IR1" ...
##  $ LandContour : chr  "Lvl" "Lvl" "Lvl" "Lvl" ...
##  $ Utilities   : chr  "AllPub" "AllPub" "AllPub" "AllPub" ...
```

```

## $ LotConfig      : chr "Inside" "FR2" "Inside" "Corner" ...
## $ LandSlope      : chr "Gtl" "Gtl" "Gtl" "Gtl" ...
## $ Neighborhood   : chr "CollgCr" "Veenker" "CollgCr" "Crawfor" ...
## $ Condition1     : chr "Norm" "Feedr" "Norm" "Norm" ...
## $ Condition2     : chr "Norm" "Norm" "Norm" "Norm" ...
## $ BldgType       : chr "1Fam" "1Fam" "1Fam" "1Fam" ...
## $ HouseStyle     : chr "2Story" "1Story" "2Story" "2Story" ...
## $ OverallQual    : int 7 6 7 7 8 5 8 7 7 5 ...
## $ OverallCond    : int 5 8 5 5 5 5 5 6 5 6 ...
## $ YearBuilt      : int 2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 ...
## $ YearRemodAdd   : int 2003 1976 2002 1970 2000 1995 2005 1973 1950 1950 ...
## $ RoofStyle      : chr "Gable" "Gable" "Gable" "Gable" ...
## $ RoofMatl       : chr "CompShg" "CompShg" "CompShg" "CompShg" ...
## $ Exterior1st    : chr "VinylSd" "MetalSd" "VinylSd" "Wd Sdng" ...
## $ Exterior2nd    : chr "VinylSd" "MetalSd" "VinylSd" "Wd Shng" ...
## $ ExterQual      : chr "Gd" "TA" "Gd" "TA" ...
## $ ExterCond      : chr "TA" "TA" "TA" "TA" ...
## $ Foundation     : chr "PConc" "CBlock" "PConc" "BrkTil" ...
## $ BsmtFinSF1     : int 706 978 486 216 655 732 1369 859 0 851 ...
## $ BsmtFinSF2     : int 0 0 0 0 0 0 0 32 0 0 ...
## $ BsmtUnfSF      : int 150 284 434 540 490 64 317 216 952 140 ...
## $ TotalBsmtSF    : int 856 1262 920 756 1145 796 1686 1107 952 991 ...
## $ Heating        : chr "GasA" "GasA" "GasA" "GasA" ...
## $ HeatingQC      : chr "Ex" "Ex" "Ex" "Gd" ...
## $ CentralAir     : chr "Y" "Y" "Y" "Y" ...
## $ Electrical     : chr "SBrkr" "SBrkr" "SBrkr" "SBrkr" ...
## $ X1stFlrSF      : int 856 1262 920 961 1145 796 1694 1107 1022 1077 ...
## $ X2ndFlrSF      : int 854 0 866 756 1053 566 0 983 752 0 ...
## $ LowQualFinSF   : int 0 0 0 0 0 0 0 0 0 0 ...
## $ GrLivArea      : int 1710 1262 1786 1717 2198 1362 1694 2090 1774 1077 ...
## $ BsmtFullBath   : int 1 0 1 1 1 1 1 1 0 1 ...
## $ BsmtHalfBath   : int 0 1 0 0 0 0 0 0 0 0 ...
## $ FullBath       : int 2 2 2 1 2 1 2 2 2 1 ...
## $ HalfBath       : int 1 0 1 0 1 1 0 1 0 0 ...
## $ BedroomAbvGr   : int 3 3 3 3 4 1 3 3 2 2 ...
## $ KitchenAbvGr   : int 1 1 1 1 1 1 1 1 2 2 ...
## $ KitchenQual    : chr "Gd" "TA" "Gd" "Gd" ...
## $ TotRmsAbvGrd   : int 8 6 6 7 9 5 7 7 8 5 ...
## $ Functional     : chr "Typ" "Typ" "Typ" "Typ" ...
## $ Fireplaces     : int 0 1 1 1 1 0 1 2 2 2 ...
## $ GarageCars     : int 2 2 2 3 3 2 2 2 2 1 ...
## $ GarageArea     : int 548 460 608 642 836 480 636 484 468 205 ...
## $ PavedDrive     : chr "Y" "Y" "Y" "Y" ...
## $ WoodDeckSF     : int 0 298 0 0 192 40 255 235 90 0 ...
## $ OpenPorchSF    : int 61 0 42 35 84 30 57 204 0 4 ...
## $ EnclosedPorch   : int 0 0 0 272 0 0 0 228 205 0 ...
## $ X3SsnPorch     : int 0 0 0 0 0 320 0 0 0 0 ...
## $ ScreenPorch    : int 0 0 0 0 0 0 0 0 0 0 ...
## $ PoolArea       : int 0 0 0 0 0 0 0 0 0 0 ...
## $ MiscVal        : int 0 0 0 0 0 700 0 350 0 0 ...
## $ MoSold         : int 2 5 9 2 12 10 8 11 4 1 ...
## $ YrSold         : int 2008 2007 2008 2006 2008 2009 2007 2009 2008 2008 ...
## $ SaleType       : chr "WD" "WD" "WD" "WD" ...
## $ SaleCondition   : chr "Normal" "Normal" "Normal" "Abnorml" ...

```

```
## $ SalePrice      : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

To analyze the data, we will need to create a model using the `lm()` function, where will be using `SalePrice` to compare our other fields. Using the model, we can use `summary()` to find better information about our model, such as R^2 .

```
model <- lm(SalePrice ~., data=train_data)
summary(model)
```

```
##
## Call:
## lm(formula = SalePrice ~ ., data = train_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -174309  -10535        0     9742   174309
##
## Coefficients: (3 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.199e+06  1.066e+06  -1.125  0.260855
## Id             6.358e-01  1.603e+00   0.397  0.691694
## MSSubClass    -7.830e+00  8.553e+01  -0.092  0.927077
## MSZoningFV     3.101e+04  1.225e+04   2.532  0.011470 *
## MSZoningRH     2.371e+04  1.232e+04   1.925  0.054412 .
## MSZoningRL     2.588e+04  1.051e+04   2.463  0.013909 *
## MSZoningRM     2.503e+04  9.852e+03   2.541  0.011174 *
## LotArea        7.006e-01  1.083e-01   6.470  1.40e-10 ***
## StreetPave     3.867e+04  1.229e+04   3.148  0.001685 **
## LotShapeIR2     4.618e+03  4.323e+03   1.068  0.285624
## LotShapeIR3     4.584e+03  9.063e+03   0.506  0.613065
## LotShapeReg     5.589e+02  1.667e+03   0.335  0.737481
## LandContourHLS  1.350e+04  5.308e+03   2.543  0.011098 *
## LandContourLow -4.241e+03  6.530e+03  -0.650  0.516119
## LandContourLvl  7.073e+03  3.822e+03   1.851  0.064427 .
## UtilitiesNoSeWa -3.037e+04  2.663e+04  -1.141  0.254268
## LotConfigCulDSac  7.629e+03  3.328e+03   2.293  0.022033 *
## LotConfigFR2    -5.847e+03  4.160e+03  -1.406  0.160105
## LotConfigFR3    -1.349e+04  1.309e+04  -1.031  0.302943
## LotConfigInside -1.241e+03  1.811e+03  -0.685  0.493217
## LandSlopeMod     1.046e+04  4.044e+03   2.586  0.009824 **
## LandSlopeSev    -2.560e+04  1.111e+04  -2.305  0.021326 *
## NeighborhoodBlueste -2.735e+03  1.935e+04  -0.141  0.887666
## NeighborhoodBrDale  8.372e+03  1.113e+04   0.752  0.452231
## NeighborhoodBrkSide -2.092e+03  9.509e+03  -0.220  0.825905
## NeighborhoodClearCr -1.277e+04  9.432e+03  -1.354  0.176093
## NeighborhoodCollgCr -9.717e+03  7.337e+03  -1.324  0.185610
## NeighborhoodCrawfor  9.596e+03  8.674e+03   1.106  0.268795
## NeighborhoodEdwards -1.675e+04  8.085e+03  -2.072  0.038477 *
## NeighborhoodGilbert -1.388e+04  7.854e+03  -1.767  0.077484 .
## NeighborhoodIDOTRR -7.806e+03  1.087e+04  -0.718  0.472893
## NeighborhoodMeadowV -1.365e+03  1.141e+04  -0.120  0.904805
## NeighborhoodMitchel -2.038e+04  8.281e+03  -2.461  0.013996 *
## NeighborhoodNames -1.447e+04  7.905e+03  -1.831  0.067377 .
## NeighborhoodNoRidge  2.877e+04  8.406e+03   3.423  0.000640 ***
## NeighborhoodNPkVill  8.163e+03  1.434e+04   0.569  0.569256
```

## NeighborhoodNridgHt	2.459e+04	7.383e+03	3.330	0.000893	***
## NeighborhoodNWAmes	-2.053e+04	8.154e+03	-2.517	0.011950	*
## NeighborhoodOldTown	-1.301e+04	9.681e+03	-1.344	0.179263	
## NeighborhoodSawyer	-1.005e+04	8.236e+03	-1.221	0.222449	
## NeighborhoodSawyerW	-6.145e+03	7.857e+03	-0.782	0.434278	
## NeighborhoodSomerst	-1.607e+01	8.984e+03	-0.002	0.998573	
## NeighborhoodStoneBr	3.896e+04	8.390e+03	4.643	3.78e-06	***
## NeighborhoodSWISU	-9.589e+03	9.837e+03	-0.975	0.329853	
## NeighborhoodTimber	-6.108e+03	8.419e+03	-0.726	0.468254	
## NeighborhoodVeenker	3.134e+03	1.074e+04	0.292	0.770436	
## Condition1Feedr	2.827e+03	5.118e+03	0.552	0.580839	
## Condition1Norm	1.210e+04	4.226e+03	2.862	0.004278	**
## Condition1PosA	7.386e+03	1.031e+04	0.716	0.473947	
## Condition1PosN	7.856e+03	7.634e+03	1.029	0.303635	
## Condition1RRAE	-1.708e+04	9.381e+03	-1.820	0.068945	.
## Condition1RRAN	6.184e+03	7.041e+03	0.878	0.379890	
## Condition1RRNE	-7.318e+03	1.839e+04	-0.398	0.690706	
## Condition1RRNN	3.829e+03	1.312e+04	0.292	0.770531	
## Condition2Feedr	-9.499e+03	2.307e+04	-0.412	0.680617	
## Condition2Norm	-7.535e+03	1.967e+04	-0.383	0.701655	
## Condition2PosA	2.022e+04	3.803e+04	0.532	0.594962	
## Condition2PosN	-2.303e+05	2.764e+04	-8.331	< 2e-16	***
## Condition2RRAE	-1.288e+05	4.688e+04	-2.747	0.006091	**
## Condition2RRAN	-1.208e+04	3.197e+04	-0.378	0.705522	
## Condition2RRNN	-8.718e+03	2.713e+04	-0.321	0.747988	
## BldgType2fmCon	-6.293e+03	1.288e+04	-0.489	0.625255	
## BldgTypeDuplex	-1.020e+03	7.466e+03	-0.137	0.891399	
## BldgTypeTwnhs	-2.560e+04	1.017e+04	-2.517	0.011949	*
## BldgTypeTwnhsE	-2.342e+04	9.215e+03	-2.542	0.011144	*
## HouseStyle1.5Unf	1.116e+04	7.941e+03	1.405	0.160212	
## HouseStyle1Story	8.915e+03	4.365e+03	2.042	0.041324	*
## HouseStyle2.5Fin	-1.711e+04	1.232e+04	-1.388	0.165250	
## HouseStyle2.5Unf	-1.188e+04	9.396e+03	-1.265	0.206181	
## HouseStyle2Story	-6.353e+03	3.558e+03	-1.785	0.074426	.
## HouseStyleSFoyer	7.609e+03	6.207e+03	1.226	0.220443	
## HouseStyleSLvl	7.253e+03	5.500e+03	1.319	0.187483	
## OverallQual	8.042e+03	1.022e+03	7.867	7.70e-15	***
## OverallCond	5.439e+03	8.759e+02	6.210	7.18e-10	***
## YearBuilt	3.307e+02	7.400e+01	4.469	8.58e-06	***
## YearRemodAdd	1.065e+02	5.571e+01	1.911	0.056168	.
## RoofStyleGable	1.518e+03	1.877e+04	0.081	0.935529	
## RoofStyleGambrel	4.328e+03	2.052e+04	0.211	0.832985	
## RoofStyleHip	3.112e+03	1.882e+04	0.165	0.868667	
## RoofStyleMansard	1.724e+04	2.186e+04	0.789	0.430398	
## RoofStyleShed	8.755e+04	3.554e+04	2.463	0.013905	*
## RoofMatlCompShg	6.504e+05	3.306e+04	19.672	< 2e-16	***
## RoofMatlMembran	7.377e+05	4.782e+04	15.427	< 2e-16	***
## RoofMatlMetal	6.978e+05	4.724e+04	14.770	< 2e-16	***
## RoofMatlRoll	6.496e+05	4.168e+04	15.583	< 2e-16	***
## RoofMatlTar&Grv	6.558e+05	3.801e+04	17.257	< 2e-16	***
## RoofMatlWdShake	6.309e+05	3.683e+04	17.132	< 2e-16	***
## RoofMatlWdShngl	7.282e+05	3.430e+04	21.229	< 2e-16	***
## Exterior1stAsphShn	-1.265e+04	3.422e+04	-0.370	0.711798	
## Exterior1stBrkComm	-1.327e+04	2.869e+04	-0.463	0.643757	

## Exterior1stBrkFace	5.438e+03	1.287e+04	0.422	0.672763	
## Exterior1stCBlock	-2.812e+04	2.761e+04	-1.018	0.308705	
## Exterior1stCemntBd	-1.490e+04	1.947e+04	-0.765	0.444353	
## Exterior1stHdBoard	-1.379e+04	1.299e+04	-1.062	0.288621	
## Exterior1stImStucc	-6.922e+04	2.863e+04	-2.418	0.015758	*
## Exterior1stMetalSd	-3.215e+03	1.483e+04	-0.217	0.828473	
## Exterior1stPlywood	-1.796e+04	1.288e+04	-1.395	0.163280	
## Exterior1stStone	-1.511e+04	2.438e+04	-0.620	0.535573	
## Exterior1stStucco	-4.992e+03	1.418e+04	-0.352	0.724787	
## Exterior1stVinylSd	-1.764e+04	1.347e+04	-1.310	0.190513	
## Exterior1stWd Sdng	-1.358e+04	1.243e+04	-1.092	0.274945	
## Exterior1stWdShng	-6.428e+03	1.344e+04	-0.478	0.632616	
## Exterior2ndAsphShn	8.090e+03	2.282e+04	0.354	0.723059	
## Exterior2ndBrk Cmn	1.496e+04	2.075e+04	0.721	0.470967	
## Exterior2ndBrkFace	-8.279e+02	1.331e+04	-0.062	0.950396	
## Exterior2ndCBlock	NA	NA	NA	NA	
## Exterior2ndCmentBd	1.303e+04	1.920e+04	0.678	0.497621	
## Exterior2ndHdBoard	8.081e+03	1.251e+04	0.646	0.518448	
## Exterior2ndImStucc	3.368e+04	1.447e+04	2.327	0.020112	*
## Exterior2ndMetalSd	2.897e+03	1.448e+04	0.200	0.841498	
## Exterior2ndOther	-6.218e+03	2.822e+04	-0.220	0.825635	
## Exterior2ndPlywood	9.189e+03	1.215e+04	0.756	0.449761	
## Exterior2ndStone	-1.015e+04	1.738e+04	-0.584	0.559203	
## Exterior2ndStucco	2.426e+03	1.366e+04	0.178	0.859056	
## Exterior2ndVinylSd	1.646e+04	1.301e+04	1.266	0.205865	
## Exterior2ndWd Sdng	1.052e+04	1.200e+04	0.877	0.380774	
## Exterior2ndWd Shng	3.419e+03	1.251e+04	0.273	0.784665	
## ExterQualFa	-8.622e+03	1.089e+04	-0.792	0.428642	
## ExterQualGd	-3.080e+04	4.794e+03	-6.425	1.86e-10	***
## ExterQualTA	-3.069e+04	5.365e+03	-5.720	1.33e-08	***
## ExterCondFa	-2.614e+03	1.888e+04	-0.138	0.889928	
## ExterCondGd	-7.990e+03	1.802e+04	-0.443	0.657627	
## ExterCondPo	1.218e+04	3.286e+04	0.371	0.711022	
## ExterCondTA	-5.344e+03	1.799e+04	-0.297	0.766449	
## FoundationCBlock	1.760e+03	3.200e+03	0.550	0.582379	
## FoundationPConc	4.829e+03	3.509e+03	1.376	0.169008	
## FoundationSlab	8.498e+03	7.864e+03	1.081	0.280108	
## FoundationStone	2.503e+03	1.118e+04	0.224	0.822878	
## FoundationWood	-3.336e+04	1.513e+04	-2.205	0.027642	*
## BsmtFinSF1	3.710e+01	4.424e+00	8.386	< 2e-16	***
## BsmtFinSF2	2.458e+01	5.800e+00	4.238	2.42e-05	***
## BsmtUnfSF	1.497e+01	4.072e+00	3.676	0.000247	***
## TotalBsmtSF	NA	NA	NA	NA	
## HeatingGasA	-7.036e+03	2.547e+04	-0.276	0.782451	
## HeatingGasW	-1.559e+04	2.627e+04	-0.594	0.552905	
## HeatingGrav	-1.540e+04	2.765e+04	-0.557	0.577754	
## HeatingOthW	-4.575e+04	3.174e+04	-1.442	0.149665	
## HeatingWall	8.292e+03	2.951e+04	0.281	0.778794	
## HeatingQCFA	-1.594e+03	4.832e+03	-0.330	0.741498	
## HeatingQCGd	-3.627e+03	2.153e+03	-1.685	0.092279	.
## HeatingQCPo	8.341e+03	2.775e+04	0.301	0.763758	
## HeatingQCTA	-4.402e+03	2.123e+03	-2.074	0.038305	*
## CentralAirY	-3.675e+03	3.999e+03	-0.919	0.358319	
## ElectricalFuseF	-1.221e+03	5.993e+03	-0.204	0.838579	

```

## ElectricalFuseP      -1.003e+04  1.745e+04  -0.574  0.565821
## ElectricalMix        3.604e+03  2.893e+04   0.125  0.900860
## ElectricalSBrkr     -1.335e+03  3.028e+03  -0.441  0.659257
## X1stFlrSF           5.503e+01  5.337e+00  10.311  < 2e-16 ***
## X2ndFlrSF           6.998e+01  5.279e+00  13.257  < 2e-16 ***
## LowQualFinSF        2.514e+01  1.873e+01   1.342  0.179809
## GrLivArea            NA          NA          NA      NA
## BsmtFullBath         1.551e+03  1.969e+03   0.788  0.431109
## BsmtHalfBath         3.517e+02  3.118e+03   0.113  0.910199
## FullBath             2.601e+03  2.247e+03   1.158  0.247210
## HalfBath            -1.508e+02  2.141e+03  -0.070  0.943878
## BedroomAbvGr        -5.506e+03  1.385e+03  -3.975  7.45e-05 ***
## KitchenAbvGr        -1.576e+04  5.776e+03  -2.729  0.006432 **
## KitchenQualFa       -2.065e+04  6.417e+03  -3.218  0.001324 **
## KitchenQualGd       -2.775e+04  3.490e+03  -7.953  4.01e-15 ***
## KitchenQualTA       -2.522e+04  3.999e+03  -6.307  3.93e-10 ***
## TotRmsAbvGrd        1.343e+03  9.765e+02   1.375  0.169414
## FunctionalMaj2      -5.309e+02  1.480e+04  -0.036  0.971397
## FunctionalMin1       4.452e+03  8.670e+03   0.514  0.607659
## FunctionalMin2       8.559e+03  8.584e+03   0.997  0.318926
## FunctionalMod       -7.249e+03  1.057e+04  -0.686  0.492877
## FunctionalSev       -5.986e+04  2.759e+04  -2.169  0.030236 *
## FunctionalTyp       1.970e+04  7.422e+03   2.654  0.008048 **
## Fireplaces          2.821e+03  1.374e+03   2.052  0.040326 *
## GarageCars          4.257e+03  2.222e+03   1.916  0.055637 .
## GarageArea          1.337e+01  7.653e+00   1.748  0.080774 .
## PavedDriveP        -3.332e+03  5.577e+03  -0.598  0.550237
## PavedDriveY        -2.109e+03  3.459e+03  -0.610  0.542108
## WoodDeckSF          1.370e+01  5.958e+00   2.300  0.021622 *
## OpenPorchSF         1.212e+01  1.185e+01   1.023  0.306696
## EnclosedPorch       5.632e+00  1.285e+01   0.438  0.661311
## X3SsnPorch          2.423e+01  2.316e+01   1.046  0.295536
## ScreenPorch         3.717e+01  1.260e+01   2.950  0.003238 **
## PoolArea            7.127e+01  1.836e+01   3.883  0.000109 ***
## MiscVal             -3.146e-01  1.470e+00  -0.214  0.830518
## MoSold              -6.394e+02  2.542e+02  -2.516  0.011996 *
## YrSold              -1.758e+02  5.250e+02  -0.335  0.737816
## SaleTypeCon          3.537e+04  1.839e+04   1.923  0.054645 .
## SaleTypeConLD        1.673e+04  1.002e+04   1.669  0.095317 .
## SaleTypeConLI        9.984e+03  1.192e+04   0.837  0.402591
## SaleTypeConLw       -2.443e+03  1.243e+04  -0.197  0.844222
## SaleTypeCWD          2.316e+04  1.337e+04   1.732  0.083534 .
## SaleTypeNew          3.440e+04  1.606e+04   2.142  0.032353 *
## SaleTypeOth          1.856e+04  1.504e+04   1.234  0.217488
## SaleTypeWD           4.603e+02  4.344e+03   0.106  0.915627
## SaleConditionAdjLand  1.047e+04  1.506e+04   0.696  0.486792
## SaleConditionAlloca  5.064e+03  8.787e+03   0.576  0.564546
## SaleConditionFamily -1.338e+03  6.330e+03  -0.211  0.832625
## SaleConditionNormal  6.618e+03  2.994e+03   2.210  0.027273 *
## SaleConditionPartial -9.139e+03  1.547e+04  -0.591  0.554858
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 24010 on 1268 degrees of freedom

```

```
## (1 observation deleted due to missingness)
## Multiple R-squared:  0.9206, Adjusted R-squared:  0.9087
## F-statistic: 77.37 on 190 and 1268 DF,  p-value: < 2.2e-16
```

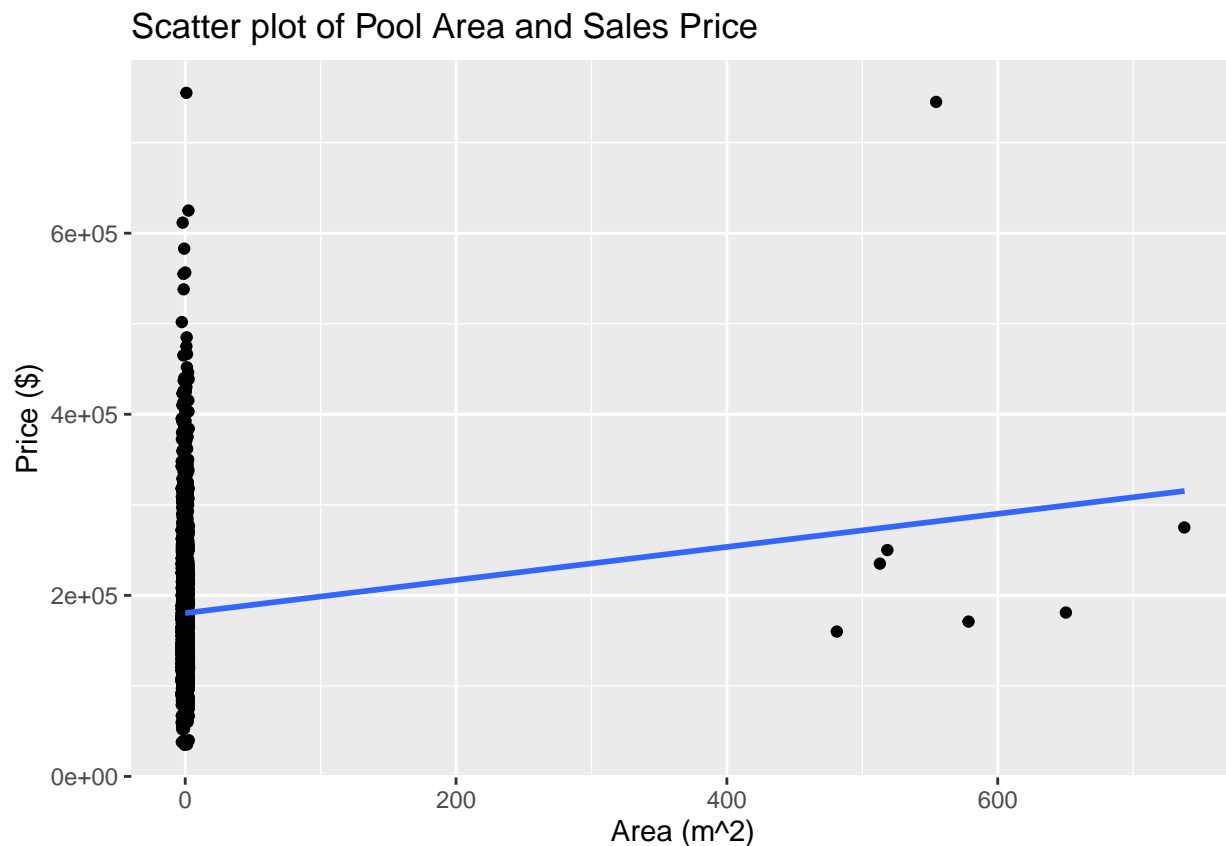
With the summary we can see that we have $R^2 = 0.9206$, and we can make some of the following interpretations when comparing SalesPrice with some of the most significant fields marked with ***: Whenever the sales price increases by one dollar...

- PoolArea: the pool's area will increase by $71.27m^2$.
- OverallQual: the overall quality will increase by \$8042.
- OverallCond: the overall condition will increase by \$5439.
- LotArea: the lot's area will increase by $0.701m^2$.

For a better visual we will be plotting graphs between the sale price and significant fields.

```
# Plot between PoolArea and SalePrice
ggplot(data = train_data, aes(x = PoolArea, y = SalePrice)) +
  geom_jitter() + geom_smooth(method = "lm", se = FALSE) +
  labs(title="Scatter plot of Pool Area and Sales Price", x="Area (m^2)",y="Price ($)")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
# Plot between RoofMatl and SalePrice
ggplot(data = train_data, aes(x = RoofMatl, y = SalePrice)) +
  geom_jitter() + geom_smooth(method = "lm", se = FALSE) +
  labs(title="Plot of Roof Material and Sales Price", x="Roof Material",y="Price ($)")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

Plot of Roof Material and Sales Price

