

# Kaggle House Prices

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## Inspección de los datos

```
updatePartitions <- function() {  
  train.size <- nrow(train)  
  full.set.size <- nrow(full.set)  
  
  train <-<- full.set[c(1:train.size), ]  
  test <-<- full.set[c((train.size + 1):full.set.size), ]  
}
```

Las dimensiones del conjunto de entrenamiento son las siguientes:

```
dim(train)
```

```
## [1] 1460    81
```

```
dim(test)
```

```
## [1] 1459    80
```

```
dim(full.set)
```

```
## [1] 2919    81
```

A continuacin, procedemos a examinar las variables del dataset:

```
str(full.set)
```

```
## 'data.frame':    2919 obs. of  81 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       : Factor w/ 5 levels "C (all)","FV",...: 4 4 4 4 4 4 4 4 5 4 ...  
## $ LotFrontage    : int  65 80 68 60 84 85 75 NA 51 50 ...  
## $ LotArea        : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...  
## $ Street         : Factor w/ 2 levels "Grvl","Pave": 2 2 2 2 2 2 2 2 2 2 ...  
## $ Alley          : Factor w/ 2 levels "Grvl","Pave": NA NA NA NA NA NA NA NA NA ...  
## $ LotShape       : Factor w/ 4 levels "IR1","IR2","IR3",...: 4 4 1 1 1 1 4 1 4 4 ...  
## $ LandContour    : Factor w/ 4 levels "Bnk","HLS","Low",...: 4 4 4 4 4 4 4 4 4 4 ...  
## $ Utilities      : Factor w/ 2 levels "AllPub","NoSeWa": 1 1 1 1 1 1 1 1 1 1 ...  
## $ LotConfig      : Factor w/ 5 levels "Corner","CulDSac",...: 5 3 5 1 3 5 5 1 5 1 ...  
## $ LandSlope      : Factor w/ 3 levels "Gtl","Mod","Sev": 1 1 1 1 1 1 1 1 1 1 ...  
## $ Neighborhood   : Factor w/ 25 levels "Blmngtn","Blueste",...: 6 25 6 7 14 12 21 17 18 4 ...  
## $ Condition1     : Factor w/ 9 levels "Artery","Feedr",...: 3 2 3 3 3 3 3 5 1 1 ...  
## $ Condition2     : Factor w/ 8 levels "Artery","Feedr",...: 3 3 3 3 3 3 3 3 1 ...  
## $ BldgType       : Factor w/ 5 levels "1fam","2fmCon",...: 1 1 1 1 1 1 1 1 1 2 ...  
## $ HouseStyle     : Factor w/ 8 levels "1.5Fin","1.5Unf",...: 6 3 6 6 6 1 3 6 1 2 ...  
## $ 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      : Factor w/ 6 levels "Flat","Gable",...: 2 2 2 2 2 2 2 2 2 ...
## $ RoofMatl       : Factor w/ 8 levels "ClyTile","CompShg",...: 2 2 2 2 2 2 2 2 2 ...
## $ Exterior1st    : Factor w/ 15 levels "AsbShng","AsphShn",...: 13 9 13 14 13 13 13 7 4 9 ...
## $ Exterior2nd    : Factor w/ 16 levels "AsbShng","AsphShn",...: 14 9 14 16 14 14 14 7 16 9 ...
## $ MasVnrType      : Factor w/ 4 levels "BrkCmn","BrkFace",...: 2 3 2 3 2 3 4 4 3 3 ...
## $ MasVnrArea      : int 196 0 162 0 350 0 186 240 0 0 ...
## $ ExterQual       : Factor w/ 4 levels "Ex","Fa","Gd",...: 3 4 3 4 3 4 3 4 4 ...
## $ ExterCond       : Factor w/ 5 levels "Ex","Fa","Gd",...: 5 5 5 5 5 5 5 5 5 ...
## $ Foundation      : Factor w/ 6 levels "BrkTil","CBlock",...: 3 2 3 1 3 6 3 2 1 1 ...
## $ BsmtQual        : Factor w/ 4 levels "Ex","Fa","Gd",...: 3 3 3 4 3 3 1 3 4 4 ...
## $ BsmtCond        : Factor w/ 4 levels "Fa","Gd","Po",...: 4 4 4 2 4 4 4 4 4 ...
## $ BsmtExposure     : Factor w/ 4 levels "Av","Gd","Mn",...: 4 2 3 4 1 4 1 3 4 4 ...
## $ BsmtFinType1     : Factor w/ 6 levels "ALQ","BLQ","GLQ",...: 3 1 3 1 3 3 3 1 6 3 ...
## $ BsmtFinSF1       : int 706 978 486 216 655 732 1369 859 0 851 ...
## $ BsmtFinType2     : Factor w/ 6 levels "ALQ","BLQ","GLQ",...: 6 6 6 6 6 6 6 2 6 6 ...
## $ 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         : Factor w/ 6 levels "Floor","GasA",...: 2 2 2 2 2 2 2 2 2 ...
## $ HeatingQC        : Factor w/ 5 levels "Ex","Fa","Gd",...: 1 1 1 3 1 1 1 1 3 1 ...
## $ CentralAir       : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 ...
## $ Electrical       : Factor w/ 5 levels "FuseA","FuseF",...: 5 5 5 5 5 5 5 5 2 5 ...
## $ 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       : Factor w/ 4 levels "Ex","Fa","Gd",...: 3 4 3 3 3 4 3 4 4 ...
## $ TotRmsAbvGrd     : int 8 6 6 7 9 5 7 7 8 5 ...
## $ Functional       : Factor w/ 7 levels "Maj1","Maj2",...: 7 7 7 7 7 7 7 3 7 ...
## $ Fireplaces        : int 0 1 1 1 1 0 1 2 2 2 ...
## $ FireplaceQu       : Factor w/ 5 levels "Ex","Fa","Gd",...: NA 5 5 3 5 NA 3 5 5 5 ...
## $ GarageType        : Factor w/ 6 levels "2Types","Attchd",...: 2 2 2 6 2 2 2 2 6 2 ...
## $ GarageYrBlt       : int 2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
## $ GarageFinish      : Factor w/ 3 levels "Fin","RFn","Unf": 2 2 2 3 2 3 2 2 3 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 ...
## $ GarageQual        : Factor w/ 5 levels "Ex","Fa","Gd",...: 5 5 5 5 5 5 5 5 2 3 ...
## $ GarageCond        : Factor w/ 5 levels "Ex","Fa","Gd",...: 5 5 5 5 5 5 5 5 5 5 ...
## $ PavedDrive        : Factor w/ 3 levels "N","P","Y": 3 3 3 3 3 3 3 3 3 3 ...
## $ 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 ...
## $ PoolQC           : Factor w/ 3 levels "Ex","Fa","Gd": NA NA NA NA NA NA NA NA NA NA ...
## $ Fence             : Factor w/ 4 levels "GdPrv","GdWo",...: NA NA NA NA NA 3 NA NA NA NA ...
## $ MiscFeature       : Factor w/ 4 levels "Gar2","Othr",...: NA NA NA NA NA 3 NA 3 NA NA ...

```

```
## $ 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     : Factor w/ 9 levels "COD","Con","ConLD",...: 9 9 9 9 9 9 9 9 9 ...
## $ SaleCondition: Factor w/ 6 levels "Abnorml","AdjLand",...: 5 5 5 1 5 5 5 5 1 5 ...
## $ SalePrice    : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

Y observamos el inicio:

```
head(full.set)
```

```
##   Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape
## 1  1          60      RL          65    8450   Pave  <NA>      Reg
## 2  2          20      RL          80    9600   Pave  <NA>      Reg
## 3  3          60      RL         11250   Pave  <NA>      IR1
## 4  4          70      RL          60    9550   Pave  <NA>      IR1
## 5  5          60      RL         14260   Pave  <NA>      IR1
## 6  6          50      RL         14115   Pave  <NA>      IR1
##   LandContour Utilities LotConfig LandSlope Neighborhood Condition1
## 1      Lvl1    AllPub    Inside      Gtl      CollgCr      Norm
## 2      Lvl1    AllPub      FR2      Gtl      Veenker      Feedr
## 3      Lvl1    AllPub    Inside      Gtl      CollgCr      Norm
## 4      Lvl1    AllPub    Corner      Gtl      Crawfor      Norm
## 5      Lvl1    AllPub      FR2      Gtl      NoRidge      Norm
## 6      Lvl1    AllPub    Inside      Gtl      Mitchel      Norm
##   Condition2 BldgType HouseStyle OverallQual OverallCond YearBuilt
## 1      Norm    1Fam    2Story           7           5      2003
## 2      Norm    1Fam    1Story           6           8      1976
## 3      Norm    1Fam    2Story           7           5      2001
## 4      Norm    1Fam    2Story           7           5      1915
## 5      Norm    1Fam    2Story           8           5      2000
## 6      Norm    1Fam    1.5Fin           5           5      1993
##   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType
## 1      2003      Gable  CompShg    VinylSd    VinylSd    BrkFace
## 2      1976      Gable  CompShg    MetalSd    MetalSd      None
## 3      2002      Gable  CompShg    VinylSd    VinylSd    BrkFace
## 4      1970      Gable  CompShg    Wd Sdng    Wd Shng      None
## 5      2000      Gable  CompShg    VinylSd    VinylSd    BrkFace
## 6      1995      Gable  CompShg    VinylSd    VinylSd      None
##   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure
## 1      196         Gd         TA      PConc      Gd         TA           No
## 2         0         TA         TA      CBlock      Gd         TA           Gd
## 3      162         Gd         TA      PConc      Gd         TA           Mn
## 4         0         TA         TA      BrkTil      TA         Gd           No
## 5      350         Gd         TA      PConc      Gd         TA           Av
## 6         0         TA         TA      Wood       Gd         TA           No
##   BsmtFinType1 BsmtFinSF1 BsmtFinType2 BsmtFinSF2 BsmtUnfSF TotalBsmtSF
## 1      GLQ       706         Unf           0        150         856
## 2      ALQ       978         Unf           0        284        1262
## 3      GLQ       486         Unf           0        434         920
## 4      ALQ       216         Unf           0        540         756
## 5      GLQ       655         Unf           0        490        1145
## 6      GLQ       732         Unf           0         64         796
##   Heating HeatingQC CentralAir Electrical X1stFlrSF X2ndFlrSF LowQualFinSF
## 1    GasA         Ex          Y      SBrkr      856      854           0
```

## 2	GasA	Ex	Y	SBrkr	1262	0	0
## 3	GasA	Ex	Y	SBrkr	920	866	0
## 4	GasA	Gd	Y	SBrkr	961	756	0
## 5	GasA	Ex	Y	SBrkr	1145	1053	0
## 6	GasA	Ex	Y	SBrkr	796	566	0
##	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	
## 1	1710	1	0	2	1	3	
## 2	1262	0	1	2	0	3	
## 3	1786	1	0	2	1	3	
## 4	1717	1	0	1	0	3	
## 5	2198	1	0	2	1	4	
## 6	1362	1	0	1	1	1	
##	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	
## 1	1	Gd	8	Typ	0	<NA>	
## 2	1	TA	6	Typ	1	TA	
## 3	1	Gd	6	Typ	1	TA	
## 4	1	Gd	7	Typ	1	Gd	
## 5	1	Gd	9	Typ	1	TA	
## 6	1	TA	5	Typ	0	<NA>	
##	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual	
## 1	Attchd	2003	RFn	2	548	TA	
## 2	Attchd	1976	RFn	2	460	TA	
## 3	Attchd	2001	RFn	2	608	TA	
## 4	Detchd	1998	Unf	3	642	TA	
## 5	Attchd	2000	RFn	3	836	TA	
## 6	Attchd	1993	Unf	2	480	TA	
##	GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	X3SsnPorch	
## 1	TA	Y	0	61	0	0	
## 2	TA	Y	298	0	0	0	
## 3	TA	Y	0	42	0	0	
## 4	TA	Y	0	35	272	0	
## 5	TA	Y	192	84	0	0	
## 6	TA	Y	40	30	0	320	
##	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold YrSold
## 1	0	0	<NA>	<NA>	<NA>	0	2 2008
## 2	0	0	<NA>	<NA>	<NA>	0	5 2007
## 3	0	0	<NA>	<NA>	<NA>	0	9 2008
## 4	0	0	<NA>	<NA>	<NA>	0	2 2006
## 5	0	0	<NA>	<NA>	<NA>	0	12 2008
## 6	0	0	<NA>	MnPrv	Shed	700	10 2009
##	SaleType	SaleCondition	SalePrice				
## 1	WD	Normal	208500				
## 2	WD	Normal	181500				
## 3	WD	Normal	223500				
## 4	WD	Abnorml	140000				
## 5	WD	Normal	250000				
## 6	WD	Normal	143000				

- Análisis de valores perdidos

```
getLostValuesStats <- function() {
  lost.count <- colSums(sapply(select(full.set, -SalePrice),
    is.na))
  lost.count <- subset(lost.count, lost.count > 0)
  lost.percentage <- (lost.count/nrow(full.set)) * 100
}
```

```

    return(data.frame(lost.count, lost.percentage))
}

```

```

getLostValuesStats()

```

```

##           lost.count lost.percentage
## MSZoning           4      0.13703323
## LotFrontage       486      16.64953751
## Alley           2721      93.21685509
## Utilities           2      0.06851662
## Exterior1st         1      0.03425831
## Exterior2nd         1      0.03425831
## MasVnrType          24      0.82219938
## MasVnrArea          23      0.78794108
## BsmtQual           81      2.77492292
## BsmtCond           82      2.80918123
## BsmtExposure        82      2.80918123
## BsmtFinType1        79      2.70640630
## BsmtFinSF1           1      0.03425831
## BsmtFinType2        80      2.74066461
## BsmtFinSF2           1      0.03425831
## BsmtUnfSF           1      0.03425831
## TotalBsmtSF          1      0.03425831
## Electrical          1      0.03425831
## BsmtFullBath         2      0.06851662
## BsmtHalfBath         2      0.06851662
## KitchenQual          1      0.03425831
## Functional          2      0.06851662
## FireplaceQu       1420     48.64679685
## GarageType          157      5.37855430
## GarageYrBlt         159      5.44707091
## GarageFinish         159      5.44707091
## GarageCars           1      0.03425831
## GarageArea           1      0.03425831
## GarageQual          159      5.44707091
## GarageCond          159      5.44707091
## PoolQC             2909     99.65741692
## Fence              2348     80.43850634
## MiscFeature         2814     96.40287770
## SaleType             1      0.03425831

```

```

lost.values.count <- full.set[, colSums(is.na(select(full.set,
  -SalePrice))) > 0]

```

```

is.lost.value <- as.data.frame(ifelse(is.na(lost.values.count),
  0, 1))

```

```

is.lost.value <- is.lost.value[, order(colSums(is.lost.value))]

```

```

is.lost.value.grid <- expand.grid(list(x = 1:nrow(is.lost.value),
  y = colnames(is.lost.value)))

```

```

is.lost.value.grid$m <- as.vector(as.matrix(is.lost.value))

```

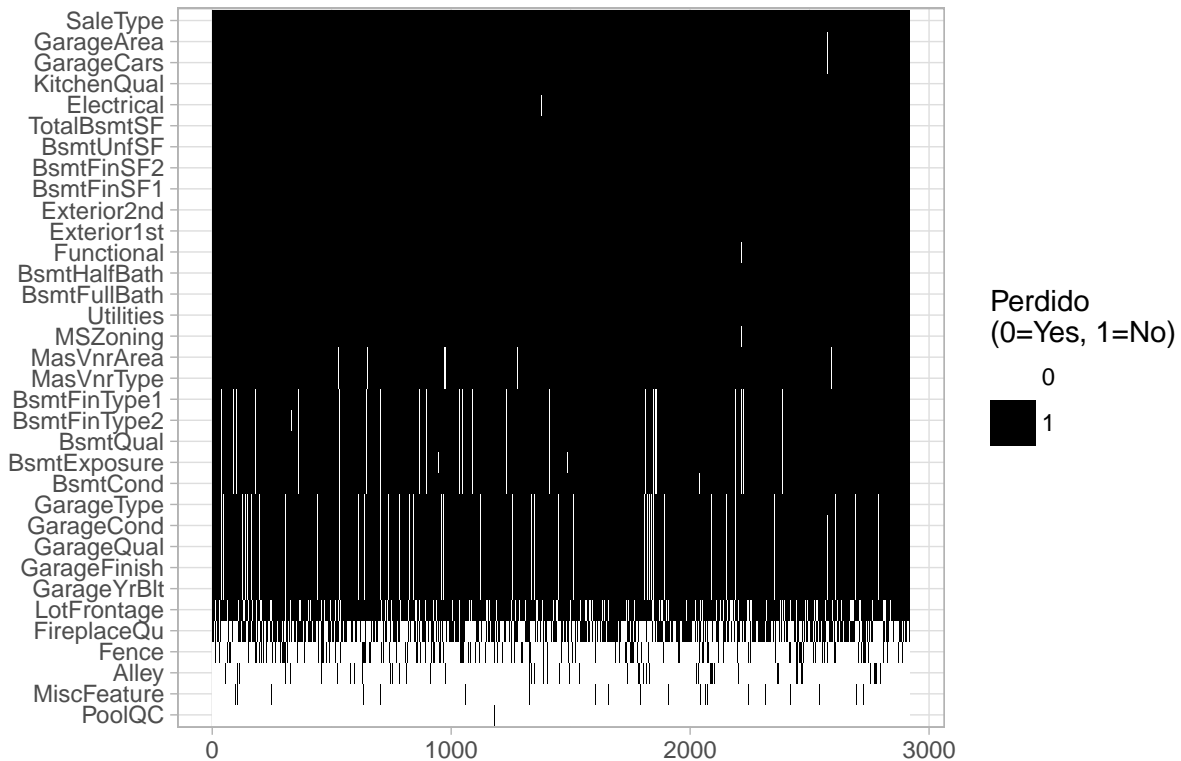
```

is.lost.value.grid <- data.frame(x = unlist(is.lost.value.grid$x),
  y = unlist(is.lost.value.grid$y), m = unlist(is.lost.value.grid$m))

```

```
ggplot2::ggplot(is.lost.value.grid) + ggplot2::geom_tile(ggplot2::aes(x = x,
y = y, fill = factor(m))) + ggplot2::scale_fill_manual(values = c("white",
"black"), name = "Perdido\n(0=Yes, 1=No)") + ggplot2::theme_light() +
ggplot2::ylab("") + ggplot2::xlab("") + ggplot2::ggtitle("Valores perdidos en el conjunto total de c
```

Valores perdidos en el conjunto total de datos

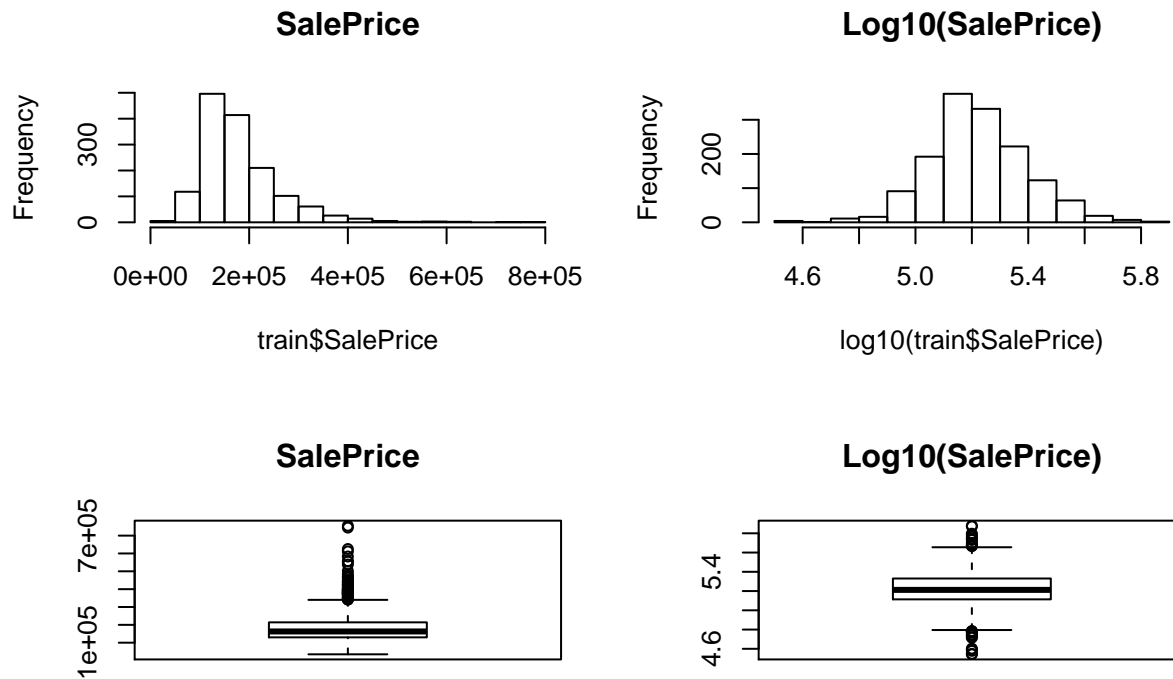


- Análisis de la distribución de la variable clase

```
par(mfrow = c(2, 2))

hist(train$SalePrice, main = "SalePrice")
hist(log10(train$SalePrice), main = "Log10(SalePrice)")

boxplot(train$SalePrice, main = "SalePrice")
boxplot(log10(train$SalePrice), main = "Log10(SalePrice)")
```



```
par(mfrow = c(1, 1))
```

- Distribución de los valores perdidos en función de la variable Log(SalePrice)

```
“{r} # TODO: DELETE ¿? lost.values.features <- rownames(getLostValuesStats()) factor.features <-  
names(train)[which(sapply(train, is.factor))] lost.values.features.factor <- dplyr::intersect(factor.features,  
lost.values.features)
```

```
plots <- lapply(lost.values.features.factor, function(feature) { categories <- train[, feature] ggplot(data =  
train, aes(x = feature, y = log(SalePrice), fill = categories)) + geom_boxplot() })
```

```
cowplot::plot_grid(plotlist = plots, ncol = 3) “
```

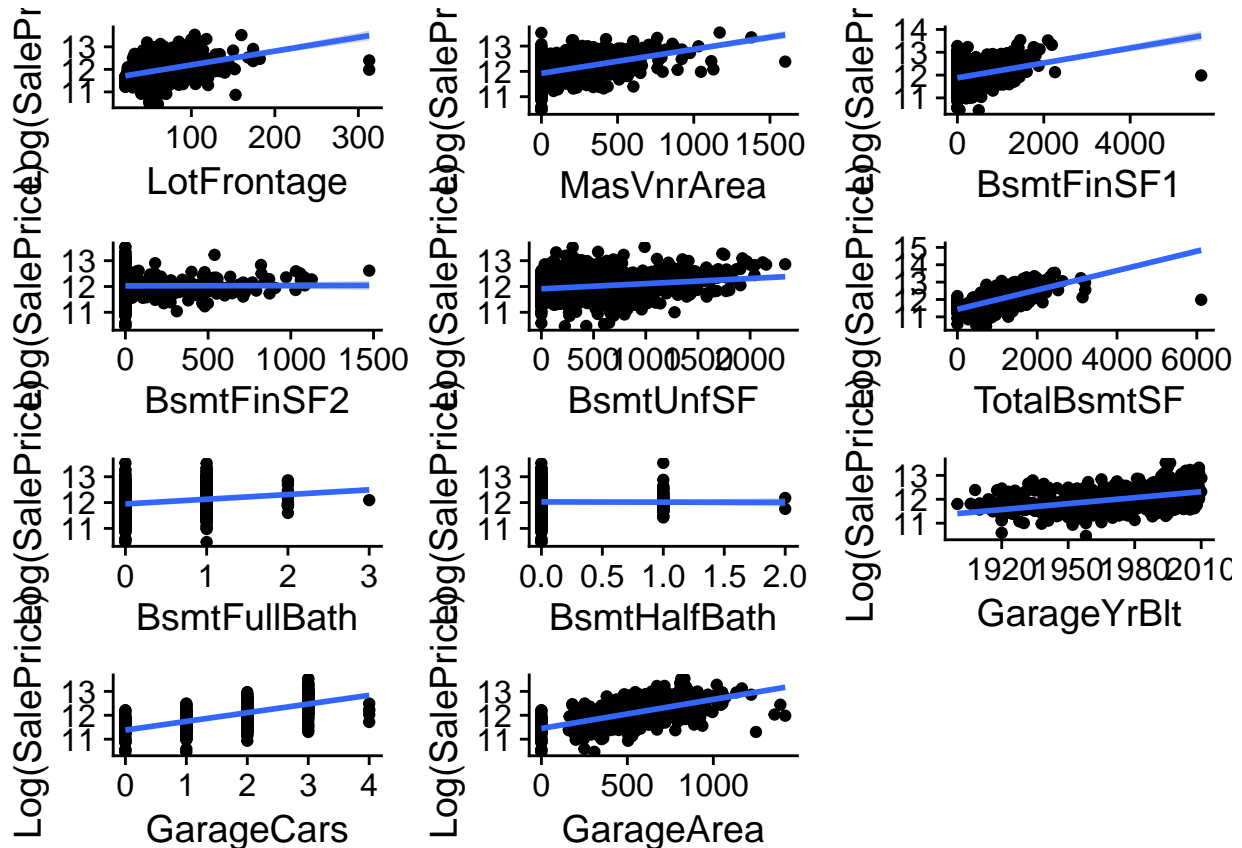
- Examinamos la distribución de las variables continuas con respecto a Log(SalePrice)

```
lost.values.features <- rownames(getLostValuesStats())  
numeric.features <- names(train)[which(sapply(train, is.numeric))]  
lost.values.features.numeric <- dplyr::intersect(numeric.features,  
lost.values.features)  
  
plots <- lapply(lost.values.features.numeric, function(feature) {  
  ggplot(data = train, aes(x = train[, feature], y = log(train$SalePrice))) +  
    geom_point() + geom_smooth(method = "lm") + xlab(label = feature) +  
    ylab(label = "Log(SalePrice)")  
})
```

```
cowplot::plot_grid(plotlist = plots, ncol = 3)
```

```
## Warning: Removed 259 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 259 rows containing missing values (geom_point).
## Warning: Removed 8 rows containing non-finite values (stat_smooth).
## Warning: Removed 8 rows containing missing values (geom_point).
## Warning: Removed 81 rows containing non-finite values (stat_smooth).
## Warning: Removed 81 rows containing missing values (geom_point).
```



## Tratamiento de los valores perdidos

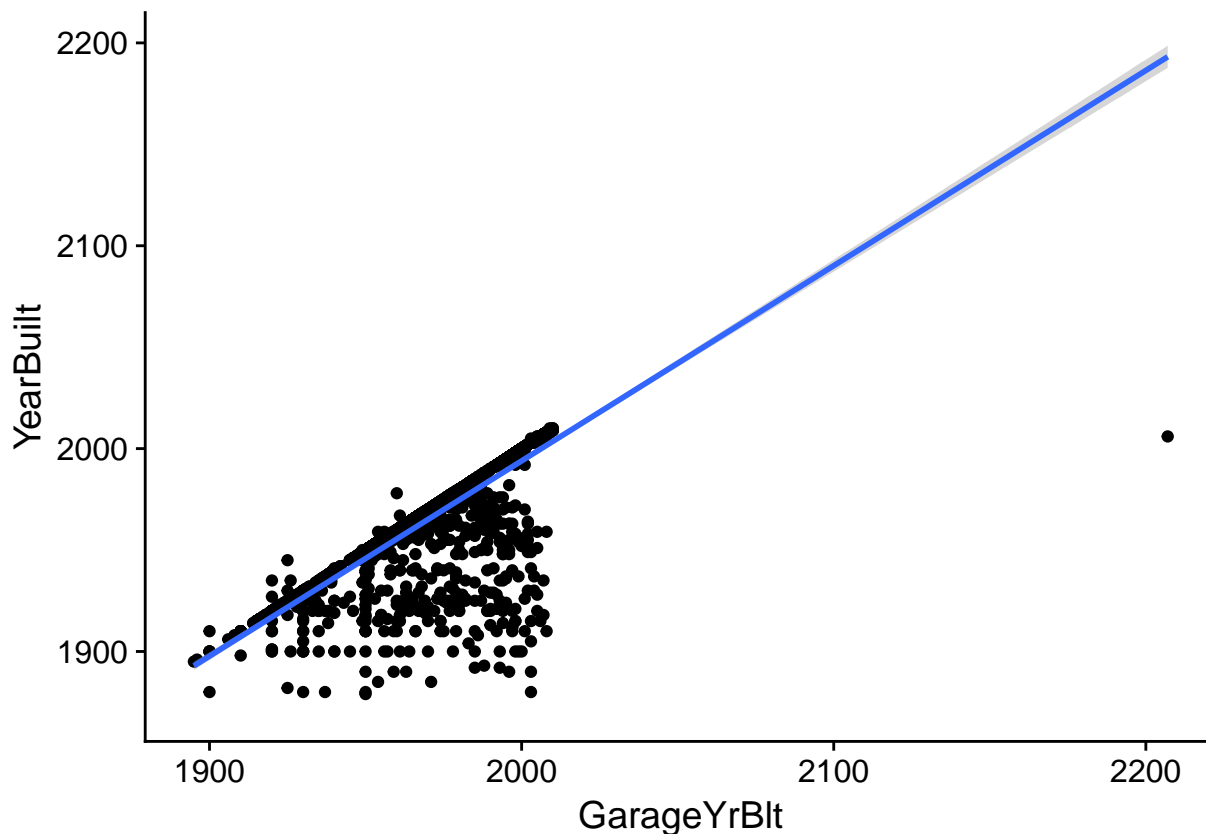
- GarageYrBlt

Se aprecia que es una propiedad que, lógicamente, está muy relacionada con YearBuilt (año de construcción). En general, se puede decir que GarageYrBlt tiende a ser igual a YearBuilt. Por consiguiente, en los valores perdidos de GarageYrBlt, se procede a asignar el correspondiente valor de YearBuilt.

```
ggplot(data = full.set, aes(x = GarageYrBlt, y = YearBuilt)) +
  geom_point() + geom_smooth(method = "lm")
```

```
## Warning: Removed 159 rows containing non-finite values (stat_smooth).
## Warning: Removed 159 rows containing missing values (geom_point).
```





```
full.set$GarageYrBlt[full.set$GarageYrBlt == 2207] <- 2007
full.set$GarageYrBlt[is.na(full.set$GarageYrBlt)] <- full.set$YearBuilt[is.na(full.set$GarageYrBlt)]

updatePartitions()
```

- LotFrontage

Por lógica, se puede decir que el área de la propiedad con la longitud de la fachada. Para confirmarlo, comprobamos la correlación entre ellas:

```
cor(full.set$LotFrontage, full.set$LotArea, use = "complete.obs")
```

```
## [1] 0.4898956
```

```
cor(log(full.set$LotFrontage), log(full.set$LotArea), use = "complete.obs")
```

```
## [1] 0.7662858
```

Y visualizamos su relación:

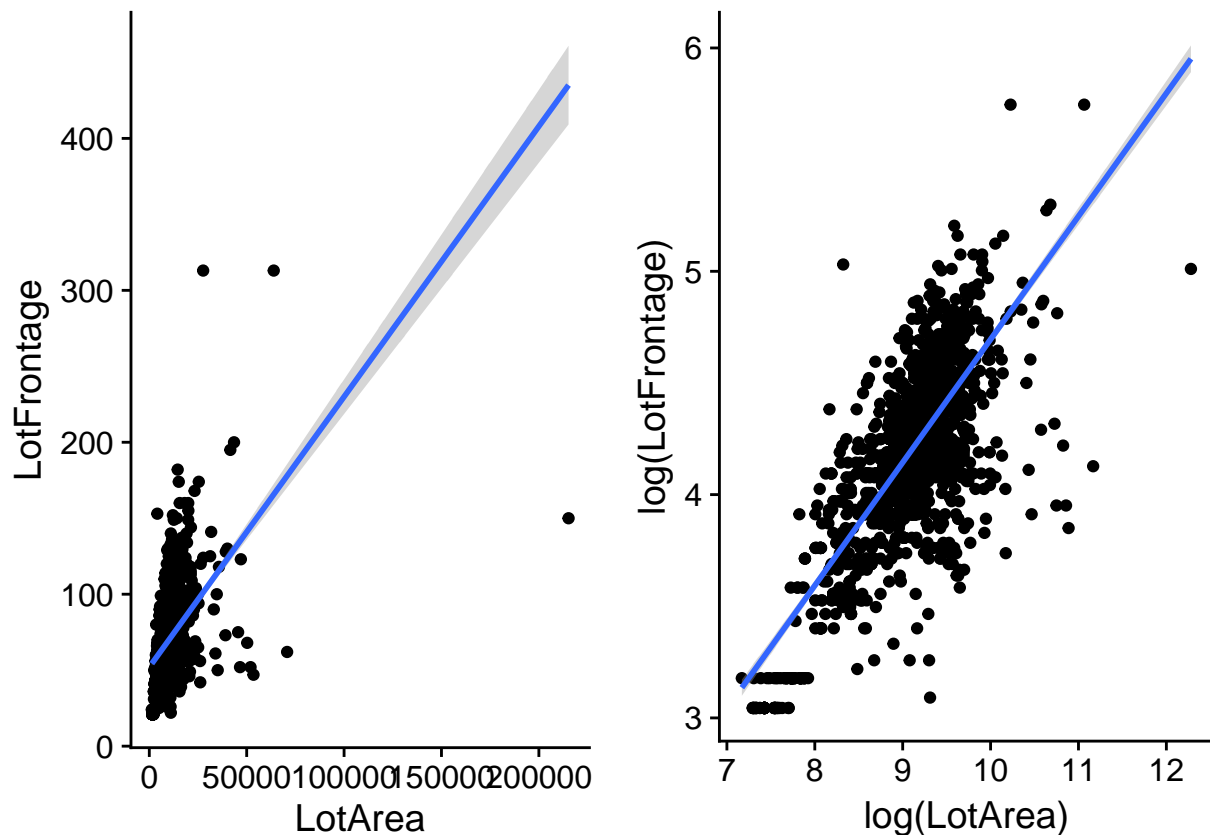
```
plotLotRelation <- ggplot(data = full.set, aes(x = LotArea, y = LotFrontage)) +
  geom_point() + geom_smooth(method = "lm")
```

```
plotLogLotRelation <- ggplot(data = full.set, aes(x = log(LotArea),
  y = log(LotFrontage))) + geom_point() + geom_smooth(method = "lm")
```

```
cowplot::plot_grid(plotLotRelation, plotLogLotRelation, ncol = 2)
```

```
## Warning: Removed 486 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 486 rows containing missing values (geom_point).
## Warning: Removed 486 rows containing non-finite values (stat_smooth).
## Warning: Removed 486 rows containing missing values (geom_point).
```



Se puede confirmar que existe una alta correlación directa entre *LotFrontage* con *LotArea*. Dado, que estas dos propiedades están relacionadas, seguramente una de ellas sea desechada en el proceso de selección de variables. Independientemente de ello, en este paso sustituiremos los valores de *LotFrontage*, por la mediana de los valores existentes.

```
full.set$LotFrontage[is.na(full.set$LotFrontage)] <- mean(full.set$LotFrontage[!is.na(full.set$LotFrontage)])
updatePartitions()
```

```
cor(full.set$LotFrontage, full.set$LotArea, use = "complete.obs")
```

```
## [1] 0.364382
```

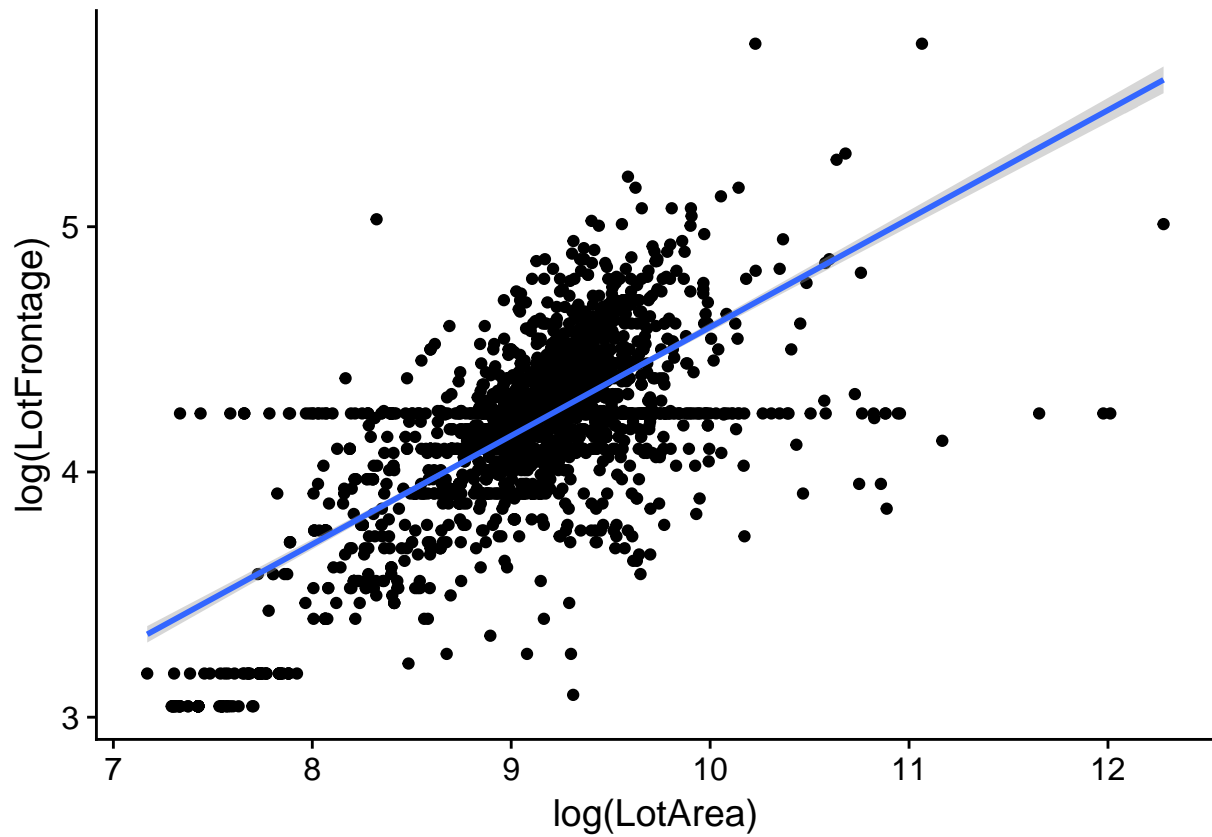
```
cor(log(full.set$LotFrontage), log(full.set$LotArea), use = "complete.obs")
```

```
## [1] 0.6894001
```

Observamos que la correlación continúa siendo similar después de tratar los valores perdidos en *LotFrontage*.

**TODO:** Quizás remplazar con la media no sea la mejor opción (cambia bastante la correlación). Si no se encuentra una solución mejor, quizás habría que cargarse directamente la variable.

```
ggplot(data = full.set, aes(x = log(LotArea), y = log(LotFrontage))) +
  geom_point() + geom_smooth(method = "lm")
```

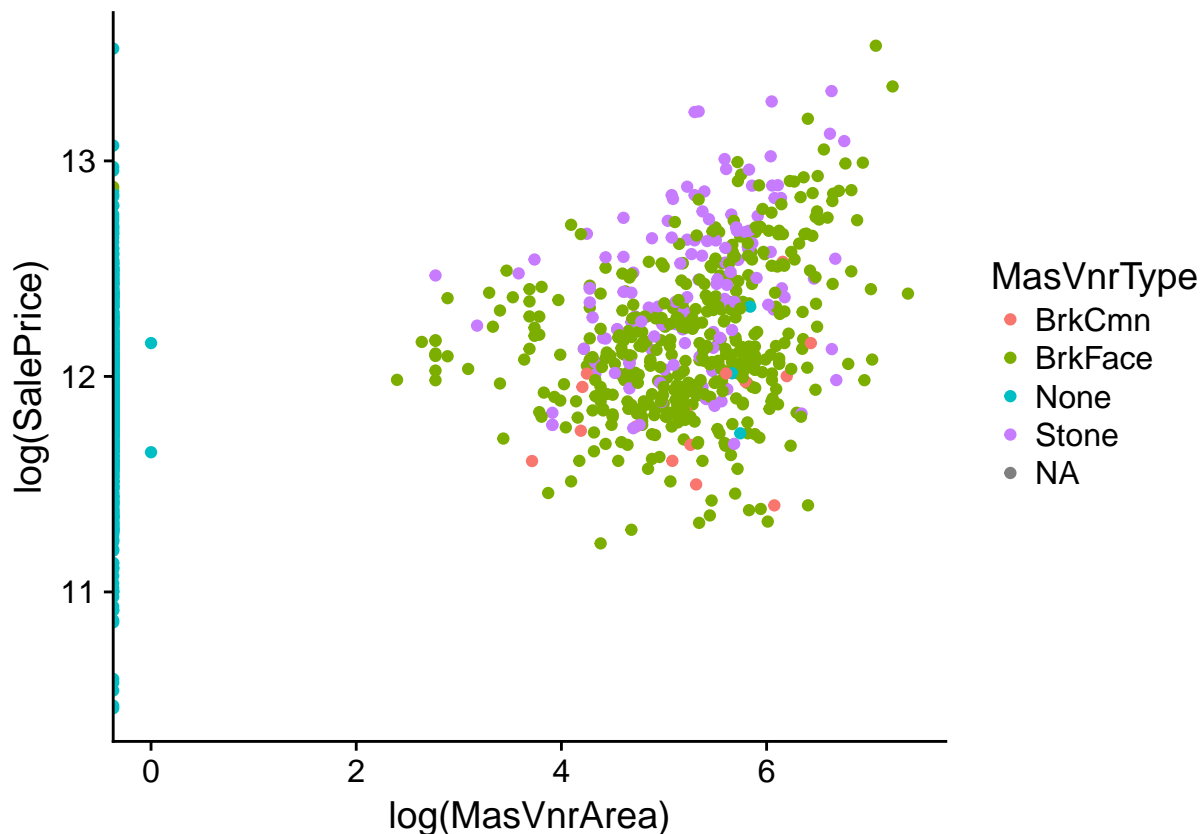


- MasVnrArea

Existe una gran cantidad de entradas con valor 0. Esto seguramente se deba a la carencia de “chapado”:

```
ggplot2::qplot(data = train, x = log(MasVnrArea), y = log(SalePrice),
  col = MasVnrType)
```

```
## Warning: Removed 8 rows containing missing values (geom_point).
```



También observamos que en ambas variables los valores perdidos (8) forman parte de los mismos ejemplos:

```
full.set$Id[is.na(full.set$MasVnrArea)]
```

```
## [1] 235 530 651 937 974 978 1244 1279 1692 1707 1883 1993 2005 2042
## [15] 2312 2326 2341 2350 2369 2593 2658 2687 2863
```

```
full.set$Id[is.na(full.set$MasVnrType)]
```

```
## [1] 235 530 651 937 974 978 1244 1279 1692 1707 1883 1993 2005 2042
## [15] 2312 2326 2341 2350 2369 2593 2611 2658 2687 2863
```

## TODO: hay una entrada más en el conjunto de test

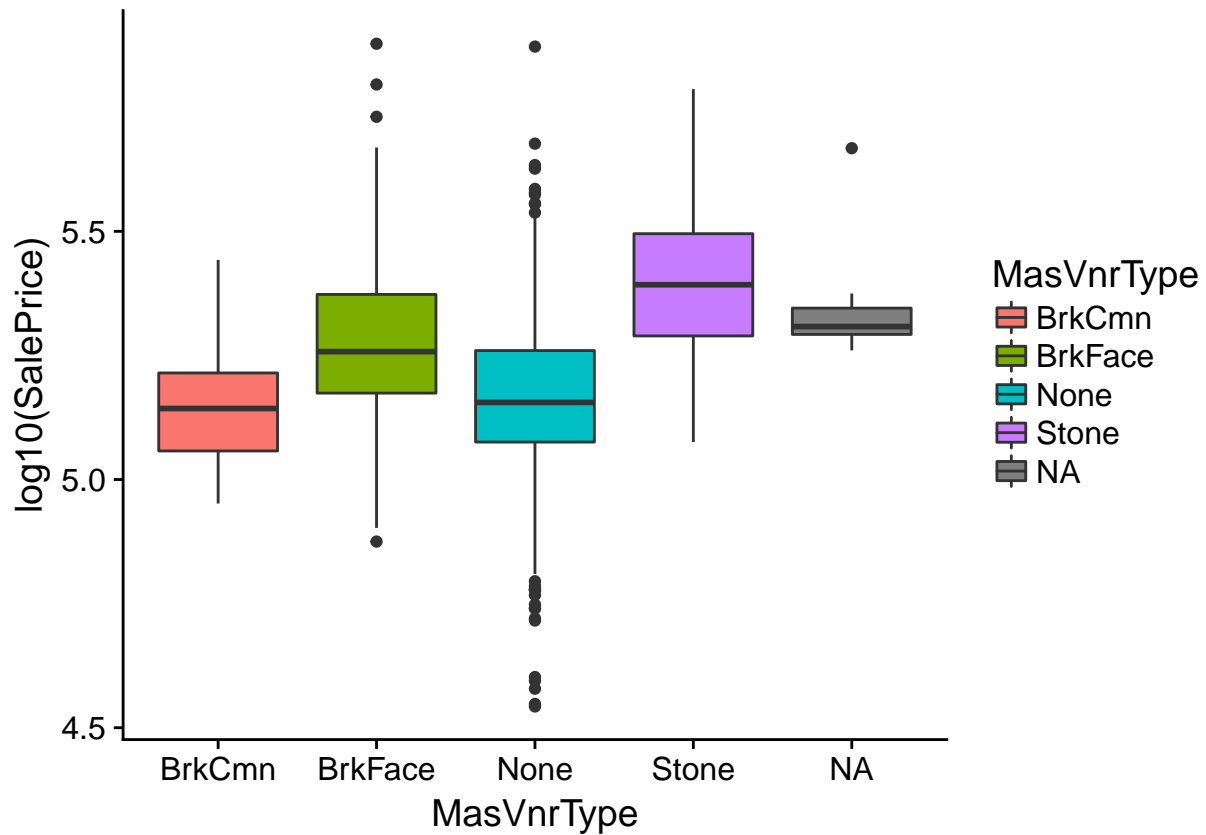
Por consiguiente, se elimina la característica *MasVnrArea*, ya que las entradas con valor 0, por ser del tipo “None”, hacen que la información desprendida de la variable esté “deformada”.

```
full.set <- dplyr::select(full.set, -MasVnrArea)
```

```
updatePartitions()
```

Ahora se deben tratar los valores perdidos de *MasVnrType*. Para ello, observamos *MasVnrType* en relación a *SalePrice* para entender su distribución.

```
qplot(data = train, x = MasVnrType, y = log10(SalePrice), geom = c("boxplot"),
      fill = MasVnrType)
```



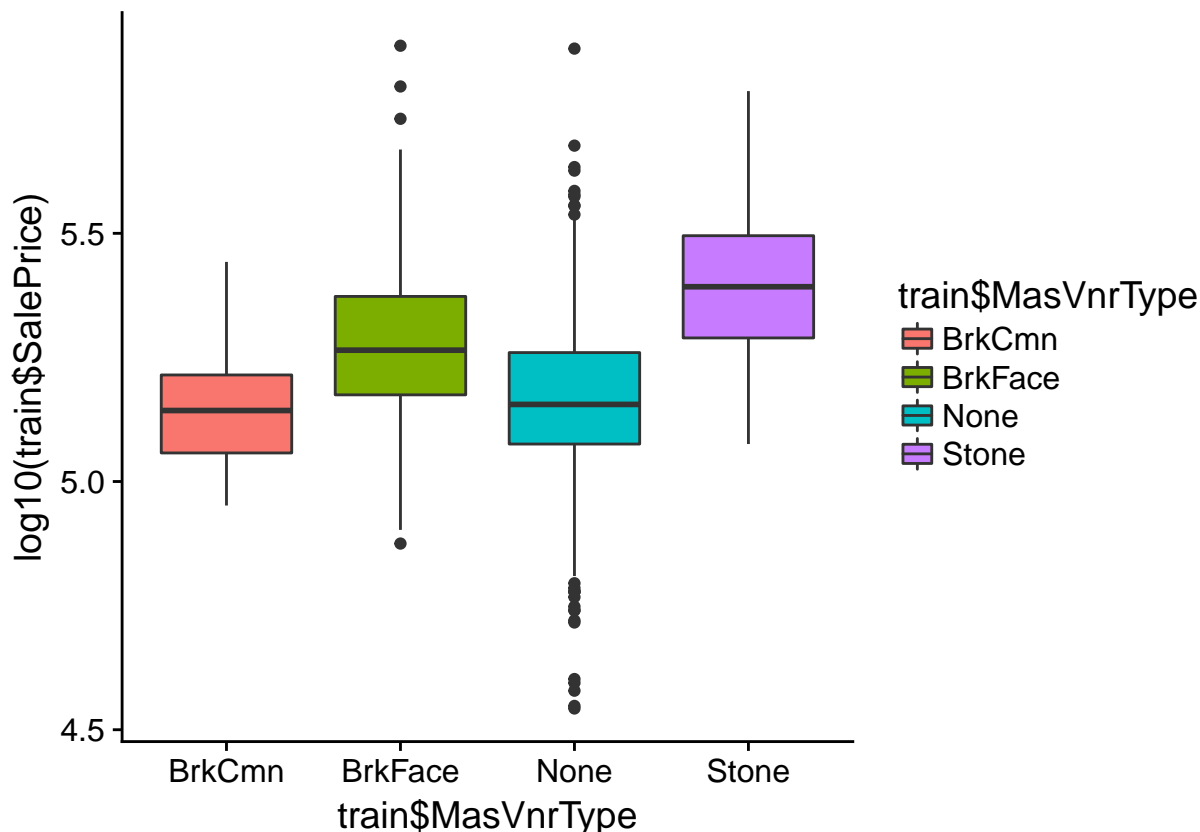
Asignamos a los valores perdidos el tipo “BrkFace”, por mayor proximidad de sus medias. Aunque también se les podría asignar el tipo “Stone”.

```
full.set$MasVnrType[is.na(full.set$MasVnrType)] <- "BrkFace"

updatePartitions()
```

Finalmente, observamos la distribución resultante en las categorías de *MasVnrType* en relación a *SalePrice*.

```
qplot(data = train, x = train$MasVnrType, y = log10(train$SalePrice),
      geom = c("boxplot"), fill = train$MasVnrType)
```



## Variables categóricas

Las siguientes características con valores perdidos se corresponden con aquellas que contienen entradas en las que hay una ausencia de la propiedad a la que representan. Por ejemplo, la propiedad *PoolQC* representa la calidad de la piscina, pero es obvio que en aquellas propiedades en las haya una ausencia de piscina, será inviable representar su calidad. Por consiguiente, se le asignarán el tipo “None” a aquellos valores ausentes (NA). Las características que contienen este tipo de valores perdidos son: *PoolQC*, *MiscFeature*, *Alley*, *Fence*, *FireplaceQu*, *GarageCond*, *GarageFinish*, *GarageQual*, *GarageType*, *BsmtCond*, *BsmtExposure*, *BsmtFinType1*, *BsmtFinType2* y *BsmtQual*.

```
categorical.features <- c("PoolQC", "MiscFeature", "Alley", "Fence",
  "FireplaceQu", "GarageCond", "GarageFinish", "GarageQual",
  "GarageType", "BsmtCond", "BsmtExposure", "BsmtFinType1",
  "BsmtFinType2", "BsmtQual")

for (feature in categorical.features) {
  if (is.factor(full.set[, feature])) {
    full.set[, feature] <- as.character(full.set[, feature])
    full.set[, feature][which(is.na(full.set[, feature]))] <- "None"
    full.set[, feature] <- factor(full.set[, feature])
  }
}

updatePartitions()
```

- Electrical

Esta característica presenta un valor perdido. Dada la mínima influencia que puede tener, se le asigna la categoría mayoritaria.

```
full.set$Electrical[is.na(full.set$Electrical)] <- as.character(sort(full.set$Electrical,
  decreasing = TRUE)[1])

updatePartitions()
```

## Corrección de valores perdidos en el conjunto de test

En primer lugar, se examinan los valores perdidos que presenta el conjunto de test y se visualizan de la misma forma que se procedió con el conjunto de entrenamiento.

```
getLostValuesStats()
```

##	lost.count	lost.percentage
## MSZoning	4	0.13703323
## Utilities	2	0.06851662
## Exterior1st	1	0.03425831
## Exterior2nd	1	0.03425831
## BsmtFinSF1	1	0.03425831
## BsmtFinSF2	1	0.03425831
## BsmtUnfSF	1	0.03425831
## TotalBsmtSF	1	0.03425831
## BsmtFullBath	2	0.06851662
## BsmtHalfBath	2	0.06851662
## KitchenQual	1	0.03425831
## Functional	2	0.06851662
## GarageCars	1	0.03425831
## GarageArea	1	0.03425831
## SaleType	1	0.03425831

**TODO:** ¿En las características que presenten valores perdidos y ya se haya examinado previamente, se proceden a tratar de la misma forma para realizar un procedimiento consistente?

Así mismo, se procede a tratar las demás variables. Por una parte, se procesan las de tipo numérico, asignando la mediana a los valores faltantes.

```
lost.test.numeric.features <- c("BsmtFinSF1", "BsmtFinSF2", "BsmtUnfSF",
  "TotalBsmtSF", "BsmtFullBath", "BsmtHalfBath", "GarageCars",
  "GarageArea")

for (feature in lost.test.numeric.features) {
  full.set[, feature][is.na(full.set[, feature])] <- median(full.set[,
    feature][!is.na(full.set[, feature])])
}

updatePartitions()
```

En cuanto a las variables de tipo nominal, se les asigna la moda de sus valores.

```
lost.test.categorical.features <- c("Exterior1st", "Exterior2nd",
  "Functional", "KitchenQual", "MSZoning", "SaleType", "Utilities")

for (feature in lost.test.categorical.features) {
  full.set[, feature][is.na(full.set[, feature])] <- as.character(sort(full.set[,
    feature], decreasing = T)[1])
}

updatePartitions()
```

Antes de continuar, comprobamos que no hay valores perdidos en ninguno de los dos conjuntos.

```
getLostValuesStats()
```

```
## [1] lost.count      lost.percentage
## <0 rows> (or 0-length row.names)
```

## Transformación de datos

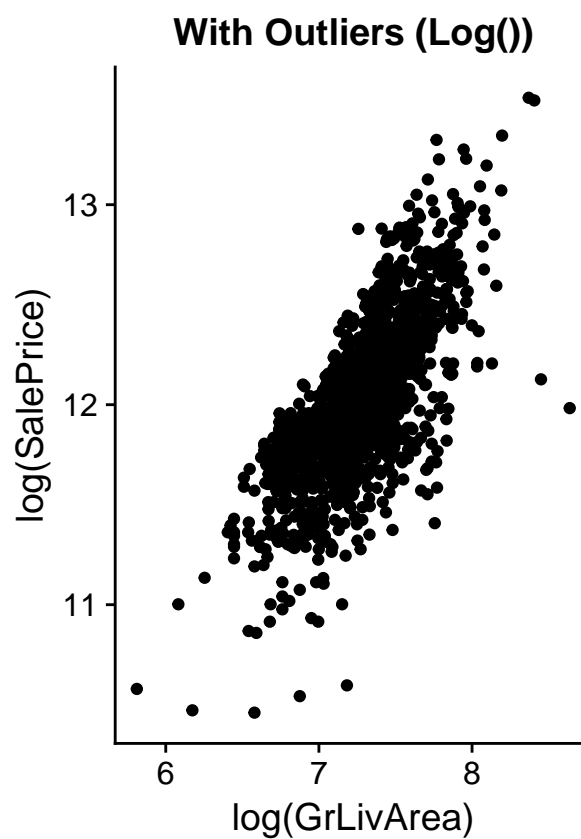
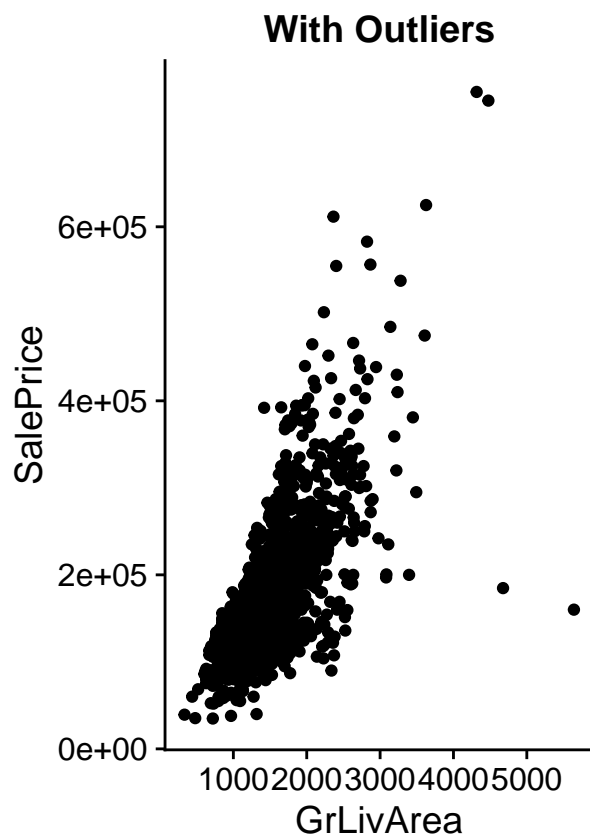
En primer lugar, se procede a eliminar la propiedad Id de los conjuntos de entrenamiento y test.

```
train.transformed <- dplyr::select(train, -Id)
test.transformed <- dplyr::select(test, -Id)
```

## Tratamiento de outliers

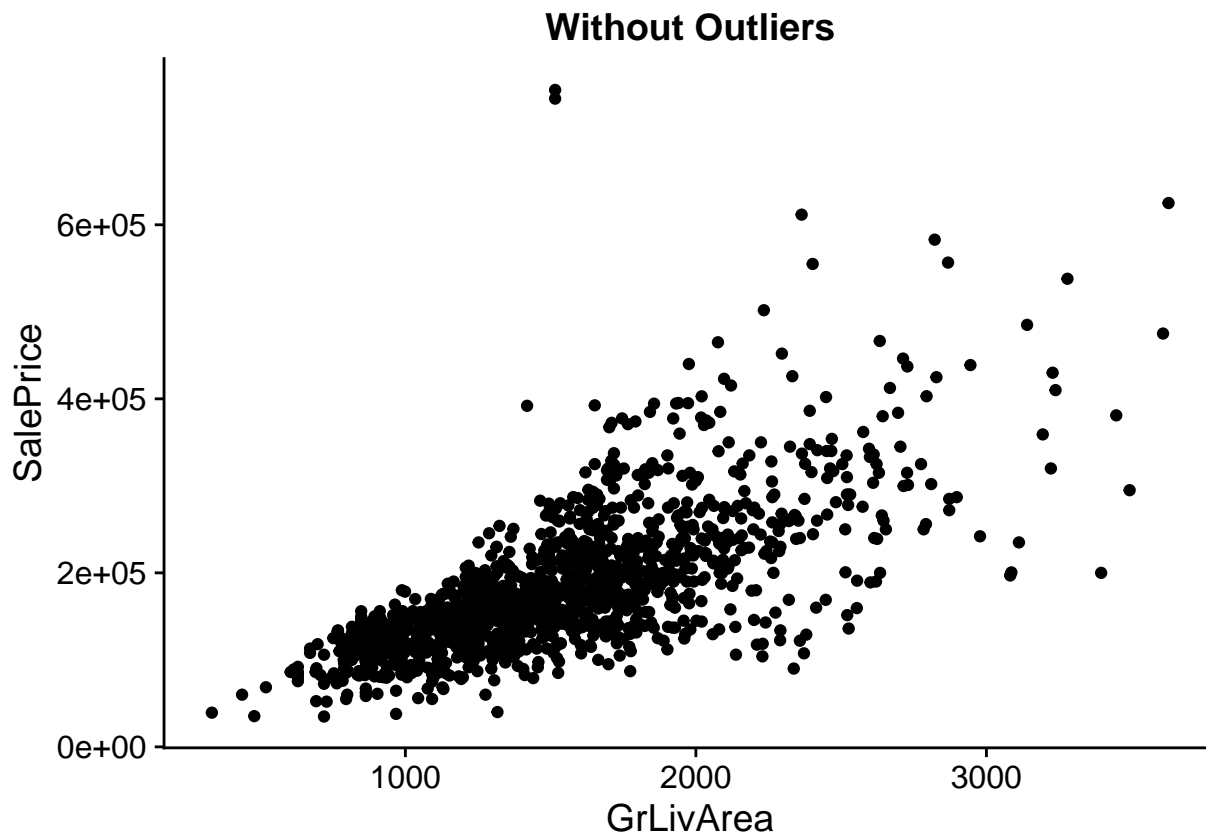
```
plot.with.outliers <- ggplot(train.transformed, aes(y = SalePrice,
  x = GrLivArea)) + ggtitle("With Outliers") + geom_point()
plot.with.outliers.log <- ggplot(train.transformed, aes(y = log(SalePrice),
  x = log(GrLivArea))) + ggtitle("With Outliers (Log())") +
  geom_point()
cowplot::plot_grid(plot.with.outliers, plot.with.outliers.log,
  ncol = 2)
```





```
train.transformed[train.transformed$GrLivArea > 4000, ]$GrLivArea <- mean(train.transformed$GrLivArea) %
  as.numeric

ggplot(train.transformed, aes(y = SalePrice, x = GrLivArea)) +
  ggtitle("Without Outliers") + geom_point()
```



```
full.set.transformed <- data.frame(data.table::rbindlist(list(train.transformed,
  test.transformed), use.names = F, fill = F))
```

- Feature engeneriing

Creación de una nueva variable: Area total basement e

```
full.set.transformed <- dplyr::select(full.set.transformed, -LotFrontage)
```

```
full.set.transformed$TotalSF = full.set.transformed$TotalBsmtSF +
  full.set.transformed$X1stFlrSF + full.set.transformed$X2ndFlrSF
```

```
full.set.transformed$Age <- full.set.transformed$YrSold - full.set.transformed$YearRemodAdd
```

```
full.set.transformed$TotalProch <- full.set.transformed$EnclosedPorch +
  full.set.transformed$ScreenPorch + full.set.transformed$X3SsnPorch
```

## Regularización de las variables continuas

Tal y como se ha mostrado, la variable *SalePrice* contiene una distribución asimétrica. Por consiguiente, para evitar el efecto que los valores extremos puedan causar, se procede a aplicar logaritmos a los valores de la distribución.

Así mismo, se procede a mostrar diagramas de densidad de cada una de las características que contengan datos numéricos. De esta forma se podrá observa que transformaciones pueden ser convenientes de hacer a cada variable.

```

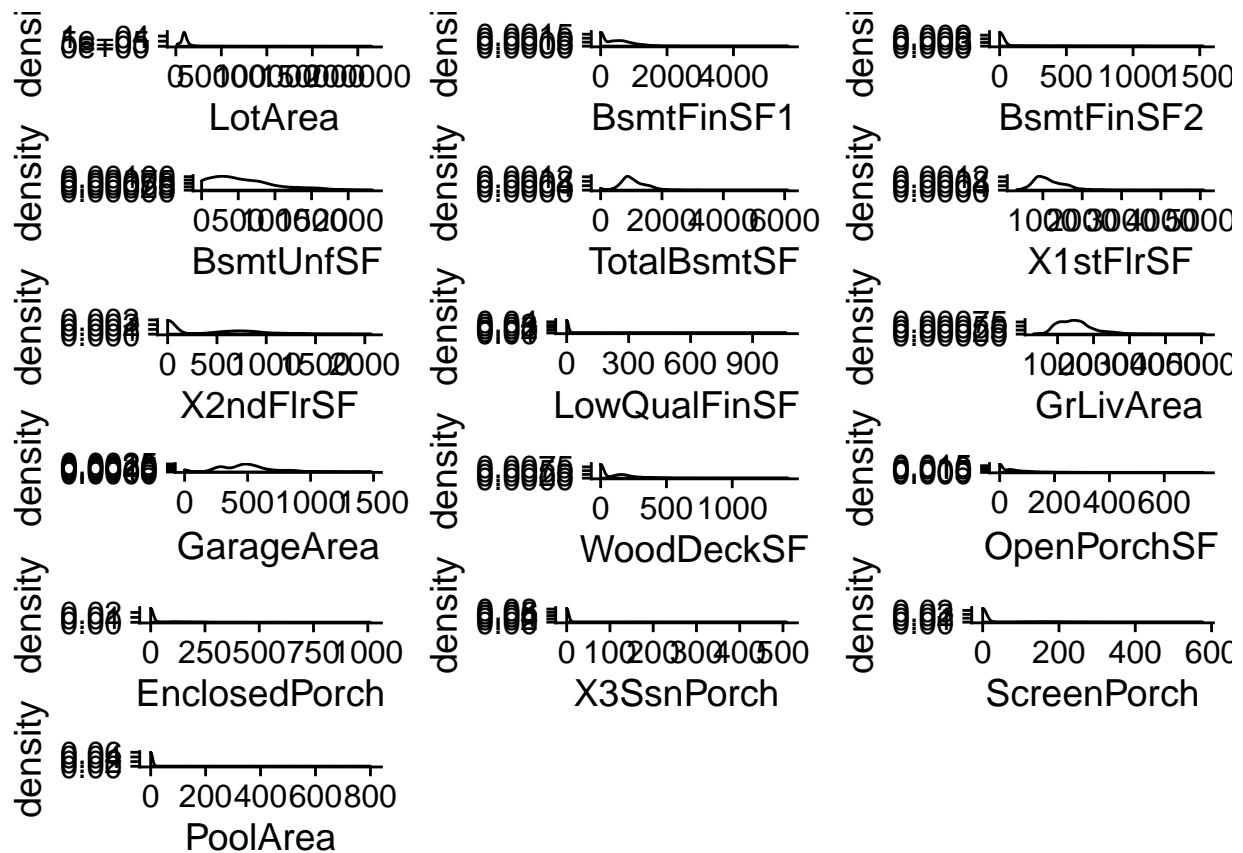
full.set.transformed$SalePrice <- log(full.set.transformed$SalePrice)

continuous.features <- c(
  "LotArea", ## Lot size in square feet
  "BsmtFinSF1", ## Type 1 finished square feet
  "BsmtFinSF2", ## Type 2 finished square feet
  "BsmtUnfSF", ## Unfinished square feet of basement area
  "TotalBsmtSF", ## Total square feet of basement area
  "X1stFlrSF", ## First Floor square feet
  "X2ndFlrSF", ## Second floor square feet
  "LowQualFinSF", ## Low quality finished square feet (all floors)
  "GrLivArea", ## Above grade (ground) living area square feet
  "GarageArea", ## Size of garage in square feet
  "WoodDeckSF", ## Wood deck area in square feet
  "OpenPorchSF", ## Open porch area in square feet
  "EnclosedPorch", ## Enclosed porch area in square feet
  "X3SsnPorch", ## Three season porch area in square feet
  "ScreenPorch", ## Screen porch area in square feet
  "PoolArea" ## Pool area in square feet
)

plots <- lapply(continuous.features, function(feature) {
  if (is.numeric(full.set.transformed[, feature])) {
    ggplot2::ggplot(data = full.set.transformed, aes(x = full.set.transformed[, feature])) +
      geom_density() +
      xlab(feature)
  }
})

cowplot::plot_grid(plotlist = plots, ncol = 3)

```

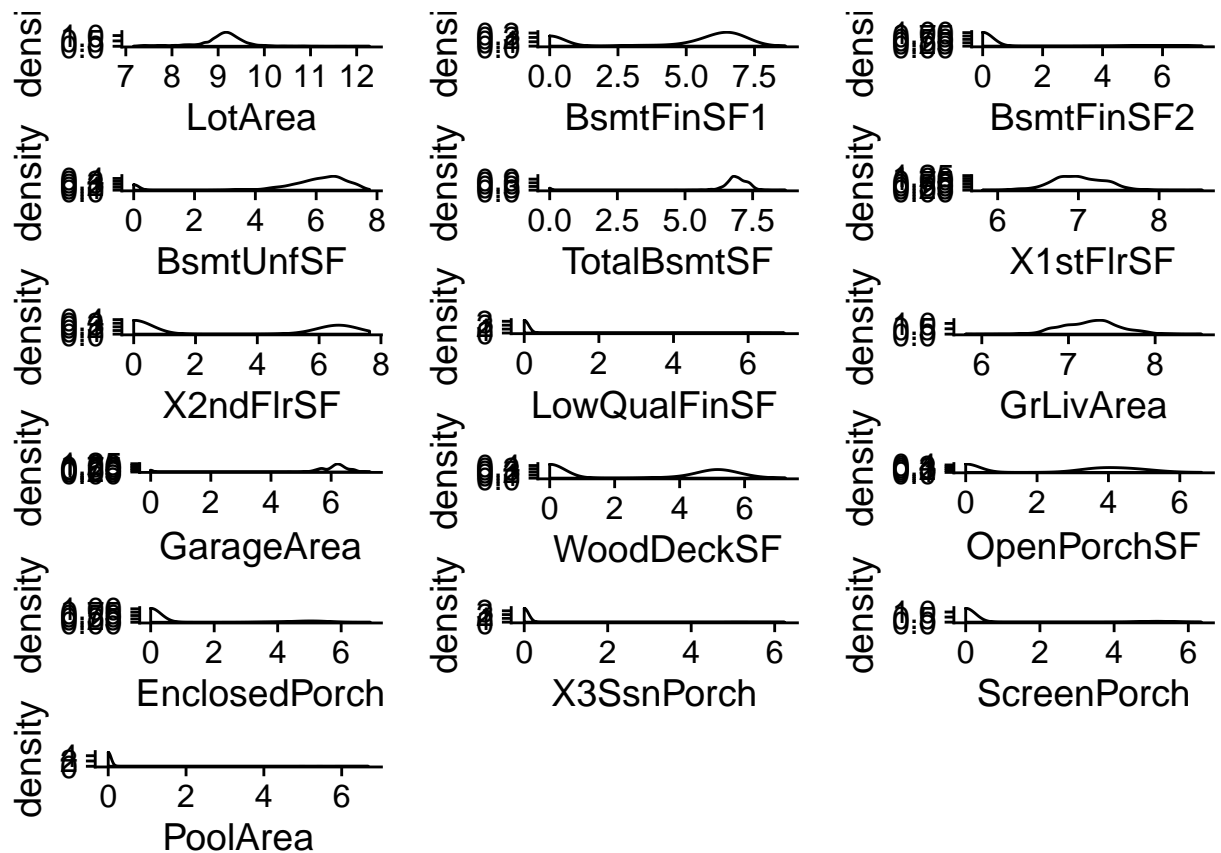


Let's normalize the continuous values

```
full.set.transformed[, continuous.features] <- log(1 + full.set.transformed[,
  continuous.features])

plots <- lapply(continuous.features, function(feature) {
  if (is.numeric(full.set.transformed[, feature])) {
    ggplot2::ggplot(data = full.set.transformed, aes(x = full.set.transformed[,
      feature])) + geom_density() + xlab(feature)
  }
})

cowplot::plot_grid(plotlist = plots, ncol = 3)
```



Center & scale...

```
full.set.preProcessed <- caret::preProcess(select(full.set.transformed,
-SalePrice), method = c("center", "scale"))
full.set.transformed <- predict(full.set.preProcessed, full.set.transformed)
```

Cambiado las variable categóricas por numéricas # TODO: Buscar explicación

```
for (i in 1:ncol(full.set.transformed)) {
  if (is.factor(full.set.transformed[, i])) {
    levels(full.set.transformed[, i]) <- c(1:length(levels(full.set.transformed[,
i])))
    full.set.transformed[, i] <- as.numeric(full.set.transformed[,
i])
  }
}
```

- Splitting into train and test

```
train.processed <- full.set.transformed[1:nrow(train.transformed),
]
test.processed <- full.set.transformed[(nrow(train.transformed) +
1):nrow(full.set.transformed), ]
test.processed <- dplyr::select(test.processed, -SalePrice)
```

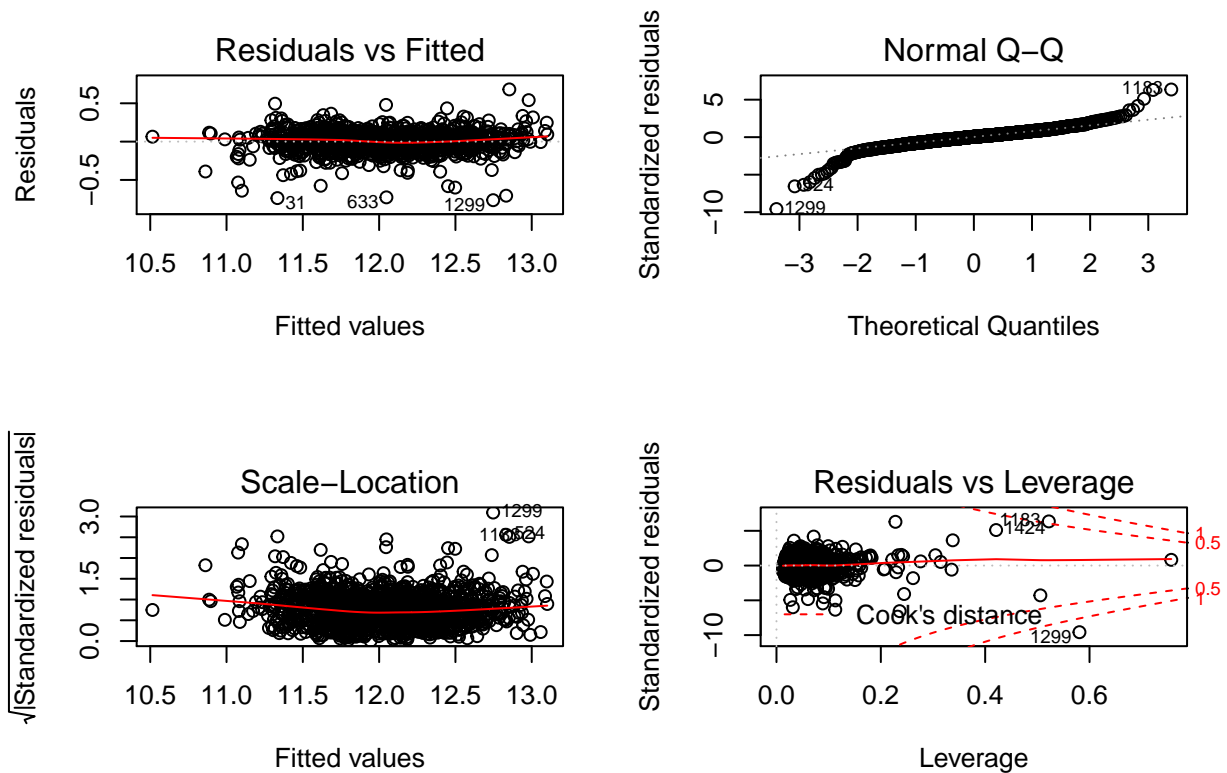
- lm

```
exploratory.lm = lm(SalePrice ~ ., data = train.processed)
```

```
par(mfrow = c(2, 2))
plot(exploratory.lm)
```

```
## Warning: not plotting observations with leverage one:
## 945
```

```
## Warning: not plotting observations with leverage one:
## 945
```



```
par(mfrow = c(1, 1))
```

```
importance <- caret::varImp(exploratory.lm)
importance.sort <- sort(importance$Overall, decreasing = TRUE,
  index.return = TRUE)

data.frame(Feature = rownames(importance)[importance.sort$ix],
  Overall = importance[importance.sort$ix, ])[1:15, ]
```

```
##      Feature Overall
## 1  GrLivArea 12.731488
## 2 OverallQual 12.235935
## 3 OverallCond 11.489647
## 4   LotArea  8.350168
## 5 SaleCondition 6.885938
## 6   Functional 6.117128
## 7   YearBuilt  5.694831
## 8   GarageCars 5.470990
```

```
## 9      PoolQC  5.435886
## 10     PoolArea 4.572355
## 11    KitchenAbvGr 4.515456
## 12     BsmtFinSF1 4.364160
## 13     KitchenQual 3.949574
## 14     Fireplaces 3.809485
## 15     X2ndFlrSF 3.751977
```

## Entrenamiento

- Entrenamiento “parcial”

```
train.processed.partition.index <- createDataPartition(train.processed$SalePrice,
  p = 0.7, list = FALSE)
train.processed.partition.train <- train.processed[train.processed.partition.index,
  ]
train.processed.partition.validation <- train.processed[-train.processed.partition.index,
  ]
```

```
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1501          nan         0.1000     0.0133
##      2         0.1370          nan         0.1000     0.0120
##      3         0.1272          nan         0.1000     0.0092
##      4         0.1176          nan         0.1000     0.0092
##      5         0.1097          nan         0.1000     0.0071
##      6         0.1033          nan         0.1000     0.0068
##      7         0.0973          nan         0.1000     0.0065
##      8         0.0920          nan         0.1000     0.0057
##      9         0.0869          nan         0.1000     0.0049
##     10         0.0817          nan         0.1000     0.0047
##     20         0.0520          nan         0.1000     0.0015
##     40         0.0306          nan         0.1000     0.0005
##     60         0.0233          nan         0.1000     0.0001
##     80         0.0200          nan         0.1000     0.0001
##    100         0.0181          nan         0.1000     0.0000
##    120         0.0169          nan         0.1000    -0.0000
##    140         0.0161          nan         0.1000    -0.0000
##    150         0.0158          nan         0.1000    -0.0001
##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1457          nan         0.1000     0.0175
##      2         0.1307          nan         0.1000     0.0138
##      3         0.1177          nan         0.1000     0.0132
##      4         0.1066          nan         0.1000     0.0105
##      5         0.0970          nan         0.1000     0.0092
##      6         0.0878          nan         0.1000     0.0083
##      7         0.0806          nan         0.1000     0.0070
##      8         0.0738          nan         0.1000     0.0064
##      9         0.0682          nan         0.1000     0.0046
##     10         0.0631          nan         0.1000     0.0043
##     20         0.0351          nan         0.1000     0.0015
##     40         0.0208          nan         0.1000     0.0001
##     60         0.0167          nan         0.1000    -0.0000
##     80         0.0145          nan         0.1000     0.0000
```

##	100	0.0132	nan	0.1000	-0.0001
##	120	0.0123	nan	0.1000	-0.0000
##	140	0.0117	nan	0.1000	-0.0001
##	150	0.0115	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1431	nan	0.1000	0.0218
##	2	0.1265	nan	0.1000	0.0162
##	3	0.1120	nan	0.1000	0.0140
##	4	0.1003	nan	0.1000	0.0114
##	5	0.0896	nan	0.1000	0.0096
##	6	0.0810	nan	0.1000	0.0087
##	7	0.0731	nan	0.1000	0.0073
##	8	0.0668	nan	0.1000	0.0060
##	9	0.0613	nan	0.1000	0.0054
##	10	0.0568	nan	0.1000	0.0037
##	20	0.0297	nan	0.1000	0.0013
##	40	0.0172	nan	0.1000	0.0001
##	60	0.0136	nan	0.1000	0.0000
##	80	0.0118	nan	0.1000	-0.0000
##	100	0.0107	nan	0.1000	-0.0001
##	120	0.0100	nan	0.1000	-0.0001
##	140	0.0094	nan	0.1000	-0.0001
##	150	0.0091	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1492	nan	0.1000	0.0135
##	2	0.1365	nan	0.1000	0.0121
##	3	0.1255	nan	0.1000	0.0094
##	4	0.1161	nan	0.1000	0.0087
##	5	0.1087	nan	0.1000	0.0080
##	6	0.1024	nan	0.1000	0.0057
##	7	0.0958	nan	0.1000	0.0057
##	8	0.0901	nan	0.1000	0.0058
##	9	0.0847	nan	0.1000	0.0052
##	10	0.0800	nan	0.1000	0.0043
##	20	0.0507	nan	0.1000	0.0016
##	40	0.0299	nan	0.1000	0.0005
##	60	0.0224	nan	0.1000	0.0001
##	80	0.0192	nan	0.1000	0.0001
##	100	0.0172	nan	0.1000	0.0000
##	120	0.0160	nan	0.1000	-0.0000
##	140	0.0151	nan	0.1000	-0.0000
##	150	0.0148	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1455	nan	0.1000	0.0168
##	2	0.1302	nan	0.1000	0.0151
##	3	0.1173	nan	0.1000	0.0128
##	4	0.1066	nan	0.1000	0.0098
##	5	0.0970	nan	0.1000	0.0091
##	6	0.0879	nan	0.1000	0.0077
##	7	0.0799	nan	0.1000	0.0075
##	8	0.0733	nan	0.1000	0.0066



##	9	0.0676	nan	0.1000	0.0049
##	10	0.0633	nan	0.1000	0.0041
##	20	0.0358	nan	0.1000	0.0014
##	40	0.0208	nan	0.1000	0.0002
##	60	0.0165	nan	0.1000	-0.0000
##	80	0.0145	nan	0.1000	0.0000
##	100	0.0133	nan	0.1000	-0.0000
##	120	0.0124	nan	0.1000	-0.0001
##	140	0.0117	nan	0.1000	-0.0001
##	150	0.0114	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1421	nan	0.1000	0.0210
##	2	0.1251	nan	0.1000	0.0154
##	3	0.1110	nan	0.1000	0.0133
##	4	0.0992	nan	0.1000	0.0123
##	5	0.0891	nan	0.1000	0.0097
##	6	0.0802	nan	0.1000	0.0087
##	7	0.0731	nan	0.1000	0.0067
##	8	0.0660	nan	0.1000	0.0066
##	9	0.0601	nan	0.1000	0.0049
##	10	0.0552	nan	0.1000	0.0048
##	20	0.0292	nan	0.1000	0.0014
##	40	0.0169	nan	0.1000	0.0000
##	60	0.0132	nan	0.1000	0.0000
##	80	0.0117	nan	0.1000	0.0000
##	100	0.0106	nan	0.1000	-0.0000
##	120	0.0098	nan	0.1000	-0.0001
##	140	0.0092	nan	0.1000	-0.0000
##	150	0.0089	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1432	nan	0.1000	0.0133
##	2	0.1316	nan	0.1000	0.0118
##	3	0.1208	nan	0.1000	0.0101
##	4	0.1123	nan	0.1000	0.0087
##	5	0.1042	nan	0.1000	0.0080
##	6	0.0973	nan	0.1000	0.0061
##	7	0.0913	nan	0.1000	0.0054
##	8	0.0861	nan	0.1000	0.0053
##	9	0.0810	nan	0.1000	0.0045
##	10	0.0770	nan	0.1000	0.0037
##	20	0.0481	nan	0.1000	0.0017
##	40	0.0281	nan	0.1000	0.0004
##	60	0.0215	nan	0.1000	0.0001
##	80	0.0186	nan	0.1000	0.0001
##	100	0.0170	nan	0.1000	0.0000
##	120	0.0159	nan	0.1000	-0.0000
##	140	0.0151	nan	0.1000	-0.0000
##	150	0.0148	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1399	nan	0.1000	0.0167
##	2	0.1249	nan	0.1000	0.0150

##	3	0.1120	nan	0.1000	0.0117
##	4	0.1017	nan	0.1000	0.0103
##	5	0.0921	nan	0.1000	0.0091
##	6	0.0841	nan	0.1000	0.0076
##	7	0.0777	nan	0.1000	0.0064
##	8	0.0710	nan	0.1000	0.0068
##	9	0.0652	nan	0.1000	0.0058
##	10	0.0597	nan	0.1000	0.0049
##	20	0.0339	nan	0.1000	0.0014
##	40	0.0196	nan	0.1000	0.0003
##	60	0.0156	nan	0.1000	0.0000
##	80	0.0137	nan	0.1000	0.0000
##	100	0.0127	nan	0.1000	-0.0001
##	120	0.0121	nan	0.1000	-0.0000
##	140	0.0114	nan	0.1000	-0.0000
##	150	0.0111	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1377	nan	0.1000	0.0183
##	2	0.1219	nan	0.1000	0.0153
##	3	0.1077	nan	0.1000	0.0138
##	4	0.0952	nan	0.1000	0.0118
##	5	0.0852	nan	0.1000	0.0094
##	6	0.0768	nan	0.1000	0.0083
##	7	0.0696	nan	0.1000	0.0066
##	8	0.0634	nan	0.1000	0.0060
##	9	0.0578	nan	0.1000	0.0053
##	10	0.0530	nan	0.1000	0.0046
##	20	0.0279	nan	0.1000	0.0011
##	40	0.0160	nan	0.1000	0.0001
##	60	0.0127	nan	0.1000	0.0000
##	80	0.0112	nan	0.1000	-0.0000
##	100	0.0101	nan	0.1000	-0.0001
##	120	0.0093	nan	0.1000	-0.0000
##	140	0.0087	nan	0.1000	-0.0001
##	150	0.0084	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1478	nan	0.1000	0.0142
##	2	0.1351	nan	0.1000	0.0117
##	3	0.1250	nan	0.1000	0.0098
##	4	0.1162	nan	0.1000	0.0083
##	5	0.1081	nan	0.1000	0.0084
##	6	0.1004	nan	0.1000	0.0074
##	7	0.0940	nan	0.1000	0.0059
##	8	0.0880	nan	0.1000	0.0055
##	9	0.0830	nan	0.1000	0.0045
##	10	0.0784	nan	0.1000	0.0043
##	20	0.0486	nan	0.1000	0.0017
##	40	0.0289	nan	0.1000	0.0004
##	60	0.0222	nan	0.1000	0.0000
##	80	0.0191	nan	0.1000	-0.0001
##	100	0.0174	nan	0.1000	0.0000
##	120	0.0162	nan	0.1000	-0.0000

```

##      140      0.0153      nan      0.1000     -0.0000
##      150      0.0150      nan      0.1000     -0.0001
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.1454      nan      0.1000      0.0179
##      2      0.1301      nan      0.1000      0.0136
##      3      0.1168      nan      0.1000      0.0135
##      4      0.1055      nan      0.1000      0.0112
##      5      0.0951      nan      0.1000      0.0107
##      6      0.0873      nan      0.1000      0.0068
##      7      0.0797      nan      0.1000      0.0074
##      8      0.0730      nan      0.1000      0.0056
##      9      0.0680      nan      0.1000      0.0043
##     10      0.0627      nan      0.1000      0.0049
##     20      0.0355      nan      0.1000      0.0014
##     40      0.0203      nan      0.1000      0.0002
##     60      0.0161      nan      0.1000     -0.0000
##     80      0.0141      nan      0.1000      0.0001
##    100      0.0129      nan      0.1000     -0.0000
##    120      0.0121      nan      0.1000     -0.0000
##    140      0.0114      nan      0.1000     -0.0000
##    150      0.0112      nan      0.1000     -0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.1413      nan      0.1000      0.0194
##      2      0.1238      nan      0.1000      0.0163
##      3      0.1091      nan      0.1000      0.0138
##      4      0.0974      nan      0.1000      0.0117
##      5      0.0869      nan      0.1000      0.0086
##      6      0.0780      nan      0.1000      0.0084
##      7      0.0707      nan      0.1000      0.0062
##      8      0.0641      nan      0.1000      0.0063
##      9      0.0588      nan      0.1000      0.0045
##     10      0.0535      nan      0.1000      0.0050
##     20      0.0285      nan      0.1000      0.0008
##     40      0.0165      nan      0.1000      0.0002
##     60      0.0133      nan      0.1000     -0.0000
##     80      0.0116      nan      0.1000     -0.0001
##    100      0.0104      nan      0.1000     -0.0001
##    120      0.0097      nan      0.1000     -0.0001
##    140      0.0091      nan      0.1000     -0.0000
##    150      0.0088      nan      0.1000     -0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.1528      nan      0.1000      0.0139
##      2      0.1399      nan      0.1000      0.0127
##      3      0.1293      nan      0.1000      0.0102
##      4      0.1200      nan      0.1000      0.0093
##      5      0.1122      nan      0.1000      0.0079
##      6      0.1048      nan      0.1000      0.0072
##      7      0.0980      nan      0.1000      0.0053
##      8      0.0923      nan      0.1000      0.0055
##      9      0.0866      nan      0.1000      0.0061
##     10      0.0822      nan      0.1000      0.0043

```

##	20	0.0521	nan	0.1000	0.0014
##	40	0.0300	nan	0.1000	0.0004
##	60	0.0223	nan	0.1000	0.0001
##	80	0.0188	nan	0.1000	-0.0000
##	100	0.0168	nan	0.1000	0.0000
##	120	0.0155	nan	0.1000	0.0000
##	140	0.0146	nan	0.1000	-0.0000
##	150	0.0142	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1483	nan	0.1000	0.0161
##	2	0.1331	nan	0.1000	0.0161
##	3	0.1202	nan	0.1000	0.0135
##	4	0.1082	nan	0.1000	0.0111
##	5	0.0973	nan	0.1000	0.0106
##	6	0.0893	nan	0.1000	0.0072
##	7	0.0815	nan	0.1000	0.0073
##	8	0.0755	nan	0.1000	0.0061
##	9	0.0691	nan	0.1000	0.0064
##	10	0.0636	nan	0.1000	0.0051
##	20	0.0351	nan	0.1000	0.0014
##	40	0.0203	nan	0.1000	0.0002
##	60	0.0158	nan	0.1000	0.0000
##	80	0.0137	nan	0.1000	0.0000
##	100	0.0125	nan	0.1000	0.0000
##	120	0.0116	nan	0.1000	-0.0001
##	140	0.0109	nan	0.1000	0.0000
##	150	0.0106	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1442	nan	0.1000	0.0199
##	2	0.1263	nan	0.1000	0.0166
##	3	0.1117	nan	0.1000	0.0145
##	4	0.1001	nan	0.1000	0.0115
##	5	0.0900	nan	0.1000	0.0105
##	6	0.0810	nan	0.1000	0.0081
##	7	0.0733	nan	0.1000	0.0066
##	8	0.0663	nan	0.1000	0.0064
##	9	0.0603	nan	0.1000	0.0052
##	10	0.0551	nan	0.1000	0.0049
##	20	0.0285	nan	0.1000	0.0011
##	40	0.0163	nan	0.1000	0.0003
##	60	0.0126	nan	0.1000	-0.0001
##	80	0.0110	nan	0.1000	-0.0001
##	100	0.0100	nan	0.1000	-0.0000
##	120	0.0091	nan	0.1000	-0.0000
##	140	0.0085	nan	0.1000	-0.0000
##	150	0.0083	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1497	nan	0.1000	0.0134
##	2	0.1372	nan	0.1000	0.0126
##	3	0.1269	nan	0.1000	0.0093
##	4	0.1176	nan	0.1000	0.0087

##	5	0.1101	nan	0.1000	0.0070
##	6	0.1027	nan	0.1000	0.0066
##	7	0.0959	nan	0.1000	0.0063
##	8	0.0900	nan	0.1000	0.0060
##	9	0.0852	nan	0.1000	0.0042
##	10	0.0811	nan	0.1000	0.0042
##	20	0.0512	nan	0.1000	0.0017
##	40	0.0297	nan	0.1000	0.0003
##	60	0.0224	nan	0.1000	0.0002
##	80	0.0188	nan	0.1000	-0.0001
##	100	0.0169	nan	0.1000	-0.0000
##	120	0.0158	nan	0.1000	0.0000
##	140	0.0149	nan	0.1000	0.0000
##	150	0.0146	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1459	nan	0.1000	0.0148
##	2	0.1308	nan	0.1000	0.0157
##	3	0.1170	nan	0.1000	0.0137
##	4	0.1052	nan	0.1000	0.0107
##	5	0.0957	nan	0.1000	0.0094
##	6	0.0880	nan	0.1000	0.0077
##	7	0.0806	nan	0.1000	0.0077
##	8	0.0741	nan	0.1000	0.0059
##	9	0.0684	nan	0.1000	0.0057
##	10	0.0635	nan	0.1000	0.0046
##	20	0.0359	nan	0.1000	0.0017
##	40	0.0200	nan	0.1000	0.0003
##	60	0.0155	nan	0.1000	0.0000
##	80	0.0133	nan	0.1000	0.0000
##	100	0.0121	nan	0.1000	-0.0001
##	120	0.0112	nan	0.1000	0.0000
##	140	0.0105	nan	0.1000	-0.0000
##	150	0.0102	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1440	nan	0.1000	0.0210
##	2	0.1266	nan	0.1000	0.0181
##	3	0.1119	nan	0.1000	0.0133
##	4	0.0996	nan	0.1000	0.0114
##	5	0.0891	nan	0.1000	0.0109
##	6	0.0802	nan	0.1000	0.0084
##	7	0.0723	nan	0.1000	0.0075
##	8	0.0663	nan	0.1000	0.0061
##	9	0.0604	nan	0.1000	0.0051
##	10	0.0551	nan	0.1000	0.0047
##	20	0.0289	nan	0.1000	0.0014
##	40	0.0161	nan	0.1000	0.0002
##	60	0.0127	nan	0.1000	-0.0001
##	80	0.0111	nan	0.1000	-0.0000
##	100	0.0101	nan	0.1000	-0.0001
##	120	0.0092	nan	0.1000	-0.0000
##	140	0.0087	nan	0.1000	-0.0001
##	150	0.0084	nan	0.1000	-0.0000

```

##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1484             nan        0.1000     0.0137
##      2         0.1360             nan        0.1000     0.0113
##      3         0.1251             nan        0.1000     0.0101
##      4         0.1164             nan        0.1000     0.0087
##      5         0.1085             nan        0.1000     0.0078
##      6         0.1005             nan        0.1000     0.0072
##      7         0.0942             nan        0.1000     0.0063
##      8         0.0885             nan        0.1000     0.0055
##      9         0.0835             nan        0.1000     0.0047
##     10         0.0788             nan        0.1000     0.0044
##     20         0.0501             nan        0.1000     0.0017
##     40         0.0303             nan        0.1000     0.0002
##     60         0.0229             nan        0.1000     0.0000
##     80         0.0194             nan        0.1000     0.0000
##    100         0.0174             nan        0.1000    -0.0001
##    120         0.0159             nan        0.1000     0.0000
##    140         0.0149             nan        0.1000    -0.0000
##    150         0.0146             nan        0.1000    -0.0001
##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1441             nan        0.1000     0.0160
##      2         0.1282             nan        0.1000     0.0155
##      3         0.1156             nan        0.1000     0.0128
##      4         0.1046             nan        0.1000     0.0109
##      5         0.0945             nan        0.1000     0.0101
##      6         0.0859             nan        0.1000     0.0088
##      7         0.0792             nan        0.1000     0.0058
##      8         0.0722             nan        0.1000     0.0066
##      9         0.0671             nan        0.1000     0.0041
##     10         0.0620             nan        0.1000     0.0046
##     20         0.0351             nan        0.1000     0.0015
##     40         0.0208             nan        0.1000     0.0002
##     60         0.0162             nan        0.1000     0.0001
##     80         0.0141             nan        0.1000     0.0001
##    100         0.0127             nan        0.1000    -0.0000
##    120         0.0118             nan        0.1000    -0.0001
##    140         0.0113             nan        0.1000     0.0000
##    150         0.0109             nan        0.1000    -0.0000
##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1424             nan        0.1000     0.0192
##      2         0.1249             nan        0.1000     0.0162
##      3         0.1106             nan        0.1000     0.0145
##      4         0.0987             nan        0.1000     0.0118
##      5         0.0883             nan        0.1000     0.0095
##      6         0.0794             nan        0.1000     0.0088
##      7         0.0720             nan        0.1000     0.0069
##      8         0.0656             nan        0.1000     0.0066
##      9         0.0602             nan        0.1000     0.0055
##     10         0.0552             nan        0.1000     0.0047
##     20         0.0295             nan        0.1000     0.0014
##     40         0.0166             nan        0.1000     0.0002

```

##	60	0.0132	nan	0.1000	0.0000
##	80	0.0115	nan	0.1000	-0.0001
##	100	0.0105	nan	0.1000	-0.0001
##	120	0.0096	nan	0.1000	-0.0000
##	140	0.0091	nan	0.1000	-0.0000
##	150	0.0087	nan	0.1000	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1449	nan	0.1000	0.0136
##	2	0.1331	nan	0.1000	0.0114
##	3	0.1235	nan	0.1000	0.0102
##	4	0.1151	nan	0.1000	0.0087
##	5	0.1071	nan	0.1000	0.0081
##	6	0.1003	nan	0.1000	0.0063
##	7	0.0937	nan	0.1000	0.0064
##	8	0.0881	nan	0.1000	0.0051
##	9	0.0833	nan	0.1000	0.0048
##	10	0.0783	nan	0.1000	0.0044
##	20	0.0503	nan	0.1000	0.0014
##	40	0.0295	nan	0.1000	0.0002
##	60	0.0228	nan	0.1000	0.0002
##	80	0.0195	nan	0.1000	0.0001
##	100	0.0177	nan	0.1000	-0.0000
##	120	0.0164	nan	0.1000	0.0000
##	140	0.0155	nan	0.1000	-0.0000
##	150	0.0152	nan	0.1000	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1400	nan	0.1000	0.0185
##	2	0.1246	nan	0.1000	0.0141
##	3	0.1123	nan	0.1000	0.0122
##	4	0.1012	nan	0.1000	0.0106
##	5	0.0926	nan	0.1000	0.0079
##	6	0.0849	nan	0.1000	0.0077
##	7	0.0775	nan	0.1000	0.0063
##	8	0.0712	nan	0.1000	0.0058
##	9	0.0660	nan	0.1000	0.0048
##	10	0.0614	nan	0.1000	0.0047
##	20	0.0352	nan	0.1000	0.0016
##	40	0.0207	nan	0.1000	0.0001
##	60	0.0165	nan	0.1000	0.0001
##	80	0.0143	nan	0.1000	-0.0000
##	100	0.0131	nan	0.1000	-0.0000
##	120	0.0125	nan	0.1000	-0.0001
##	140	0.0119	nan	0.1000	-0.0000
##	150	0.0116	nan	0.1000	-0.0001

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
----	------	---------------	---------------	----------	---------

##	1	0.1390	nan	0.1000	0.0174
##	2	0.1218	nan	0.1000	0.0176
##	3	0.1074	nan	0.1000	0.0130
##	4	0.0957	nan	0.1000	0.0113
##	5	0.0862	nan	0.1000	0.0095
##	6	0.0772	nan	0.1000	0.0084
##	7	0.0704	nan	0.1000	0.0069
##	8	0.0640	nan	0.1000	0.0056
##	9	0.0586	nan	0.1000	0.0051
##	10	0.0539	nan	0.1000	0.0043
##	20	0.0283	nan	0.1000	0.0010
##	40	0.0167	nan	0.1000	0.0001
##	60	0.0131	nan	0.1000	0.0001
##	80	0.0113	nan	0.1000	0.0000
##	100	0.0104	nan	0.1000	-0.0001
##	120	0.0096	nan	0.1000	-0.0000
##	140	0.0090	nan	0.1000	-0.0000
##	150	0.0087	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1488	nan	0.1000	0.0137
##	2	0.1368	nan	0.1000	0.0120
##	3	0.1270	nan	0.1000	0.0097
##	4	0.1182	nan	0.1000	0.0088
##	5	0.1104	nan	0.1000	0.0077
##	6	0.1032	nan	0.1000	0.0071
##	7	0.0971	nan	0.1000	0.0061
##	8	0.0913	nan	0.1000	0.0058
##	9	0.0859	nan	0.1000	0.0048
##	10	0.0817	nan	0.1000	0.0042
##	20	0.0521	nan	0.1000	0.0016
##	40	0.0303	nan	0.1000	0.0006
##	60	0.0234	nan	0.1000	0.0002
##	80	0.0200	nan	0.1000	0.0001
##	100	0.0181	nan	0.1000	-0.0000
##	120	0.0166	nan	0.1000	-0.0000
##	140	0.0157	nan	0.1000	0.0000
##	150	0.0153	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1447	nan	0.1000	0.0176
##	2	0.1288	nan	0.1000	0.0156
##	3	0.1164	nan	0.1000	0.0122
##	4	0.1057	nan	0.1000	0.0102
##	5	0.0965	nan	0.1000	0.0088
##	6	0.0873	nan	0.1000	0.0083
##	7	0.0790	nan	0.1000	0.0079
##	8	0.0721	nan	0.1000	0.0068
##	9	0.0666	nan	0.1000	0.0053
##	10	0.0620	nan	0.1000	0.0044
##	20	0.0353	nan	0.1000	0.0013
##	40	0.0206	nan	0.1000	0.0002
##	60	0.0164	nan	0.1000	0.0000
##	80	0.0144	nan	0.1000	-0.0000



##	100	0.0133	nan	0.1000	-0.0001
##	120	0.0124	nan	0.1000	-0.0001
##	140	0.0116	nan	0.1000	-0.0000
##	150	0.0113	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1422	nan	0.1000	0.0193
##	2	0.1259	nan	0.1000	0.0169
##	3	0.1109	nan	0.1000	0.0132
##	4	0.0984	nan	0.1000	0.0123
##	5	0.0879	nan	0.1000	0.0102
##	6	0.0802	nan	0.1000	0.0075
##	7	0.0729	nan	0.1000	0.0062
##	8	0.0661	nan	0.1000	0.0068
##	9	0.0606	nan	0.1000	0.0051
##	10	0.0555	nan	0.1000	0.0048
##	20	0.0305	nan	0.1000	0.0013
##	40	0.0177	nan	0.1000	0.0001
##	60	0.0139	nan	0.1000	-0.0000
##	80	0.0122	nan	0.1000	-0.0001
##	100	0.0108	nan	0.1000	-0.0000
##	120	0.0099	nan	0.1000	-0.0001
##	140	0.0091	nan	0.1000	-0.0001
##	150	0.0088	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1476	nan	0.1000	0.0133
##	2	0.1354	nan	0.1000	0.0125
##	3	0.1255	nan	0.1000	0.0099
##	4	0.1172	nan	0.1000	0.0084
##	5	0.1083	nan	0.1000	0.0079
##	6	0.1015	nan	0.1000	0.0069
##	7	0.0956	nan	0.1000	0.0056
##	8	0.0904	nan	0.1000	0.0050
##	9	0.0853	nan	0.1000	0.0051
##	10	0.0805	nan	0.1000	0.0044
##	20	0.0515	nan	0.1000	0.0015
##	40	0.0306	nan	0.1000	0.0002
##	60	0.0234	nan	0.1000	0.0002
##	80	0.0201	nan	0.1000	0.0001
##	100	0.0181	nan	0.1000	0.0000
##	120	0.0170	nan	0.1000	-0.0000
##	140	0.0160	nan	0.1000	-0.0000
##	150	0.0158	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1438	nan	0.1000	0.0175
##	2	0.1280	nan	0.1000	0.0147
##	3	0.1158	nan	0.1000	0.0119
##	4	0.1054	nan	0.1000	0.0098
##	5	0.0965	nan	0.1000	0.0093
##	6	0.0879	nan	0.1000	0.0081
##	7	0.0813	nan	0.1000	0.0076
##	8	0.0756	nan	0.1000	0.0063

```
##      9      0.0697      nan      0.1000      0.0059
##     10      0.0643      nan      0.1000      0.0049
##     20      0.0364      nan      0.1000      0.0014
##     40      0.0213      nan      0.1000      0.0002
##     60      0.0168      nan      0.1000      0.0000
##     80      0.0146      nan      0.1000     -0.0000
##    100      0.0133      nan      0.1000     -0.0000
##    120      0.0124      nan      0.1000     -0.0000
##    140      0.0118      nan      0.1000     -0.0001
##    150      0.0114      nan      0.1000     -0.0000
```

```
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.1417      nan      0.1000      0.0191
##      2      0.1253      nan      0.1000      0.0149
##      3      0.1101      nan      0.1000      0.0152
##      4      0.0984      nan      0.1000      0.0111
##      5      0.0888      nan      0.1000      0.0095
##      6      0.0800      nan      0.1000      0.0080
##      7      0.0727      nan      0.1000      0.0074
##      8      0.0659      nan      0.1000      0.0063
##      9      0.0603      nan      0.1000      0.0045
##     10      0.0556      nan      0.1000      0.0045
##     20      0.0298      nan      0.1000      0.0012
##     40      0.0172      nan      0.1000      0.0001
##     60      0.0139      nan      0.1000      0.0000
##     80      0.0124      nan      0.1000     -0.0001
##    100      0.0113      nan      0.1000     -0.0000
##    120      0.0104      nan      0.1000     -0.0001
##    140      0.0099      nan      0.1000     -0.0000
##    150      0.0096      nan      0.1000     -0.0000
```

```
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.1413      nan      0.1000      0.0222
##      2      0.1244      nan      0.1000      0.0162
##      3      0.1095      nan      0.1000      0.0140
##      4      0.0972      nan      0.1000      0.0119
##      5      0.0873      nan      0.1000      0.0091
##      6      0.0787      nan      0.1000      0.0075
##      7      0.0713      nan      0.1000      0.0070
##      8      0.0650      nan      0.1000      0.0058
##      9      0.0595      nan      0.1000      0.0055
##     10      0.0549      nan      0.1000      0.0043
##     20      0.0293      nan      0.1000      0.0011
##     40      0.0171      nan      0.1000      0.0001
##     60      0.0135      nan      0.1000     -0.0000
##     80      0.0118      nan      0.1000     -0.0000
##    100      0.0108      nan      0.1000     -0.0001
##    120      0.0100      nan      0.1000     -0.0001
##    140      0.0094      nan      0.1000     -0.0000
##    150      0.0091      nan      0.1000     -0.0001
```

```
model.partial # 0.1320744 # 0.1305035 # 1266631 # 1285614
```

```
## Stochastic Gradient Boosting
##
```

```
## 1024 samples
## 80 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 922, 923, 921, 920, 920, 922, ...
## Resampling results across tuning parameters:
##
## interaction.depth n.trees RMSE      Rsquared MAE
## 1                50      0.1682590 0.8444157 0.11670376
## 1                100      0.1485041 0.8692648 0.10203270
## 1                150      0.1417860 0.8797562 0.09726639
## 2                50      0.1505312 0.8667998 0.10385932
## 2                100      0.1372135 0.8866656 0.09459342
## 2                150      0.1352014 0.8898472 0.09223647
## 3                50      0.1427230 0.8794867 0.09913112
## 3                100      0.1352764 0.8909551 0.09232436
## 3                150      0.1340584 0.8929384 0.09098677
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were n.trees = 150,
## interaction.depth = 3, shrinkage = 0.1 and n.minobsinnode = 10.
```

- Validación del modelo

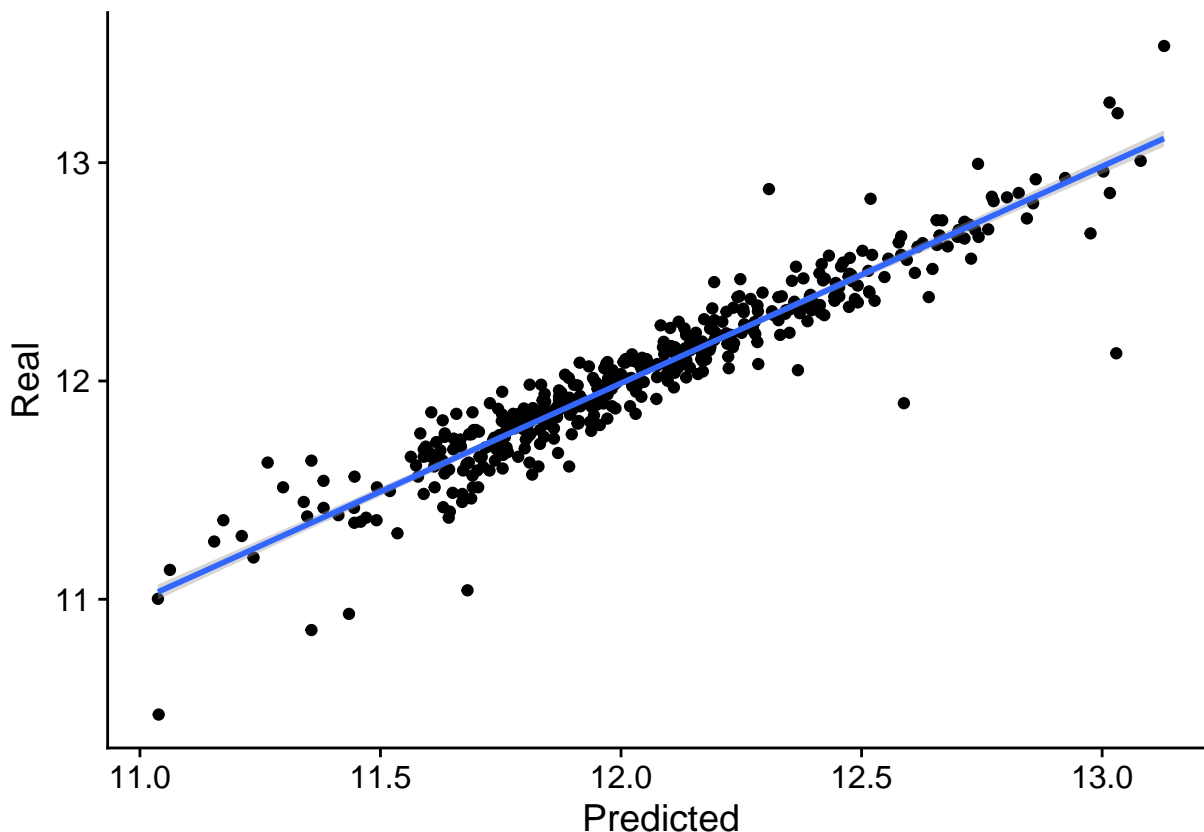
```
predictAndEvaluate <- function(model, validation.set) {
  validation.prediction <- stats::predict(model, dplyr::select(validation.set,
    -SalePrice))

  print(ggplot2::qplot(x = validation.prediction, y = validation.set$SalePrice,
    geom = c("point", "smooth"), method = "lm", xlab = "Predicted",
    ylab = "Real"))

  rmse(validation.set$SalePrice, validation.prediction)
}
```

```
predictAndEvaluate(model.partial, train.processed.partition.validation) # 0.1299482 # 0.1483049 # 0.14
```

```
## Warning: Ignoring unknown parameters: method
```



```
## [1] 0.1279009
```

Trying to improve model ...

```
ensembleTrain <- function(train.set) {
  set.seed(SEED)

  trControl <- trainControl(method = "cv", number = 7, savePredictions = "final",
    index = createResample(train.set$OverallQual, 7), allowParallel = TRUE)

  modellist <- caretEnsemble::caretList(SalePrice ~ ., data = train.set,
    trControl = trControl, metric = "RMSE", tuneList = list(gbm = caretModelSpec(method = "gbm",
      tuneGrid = expand.grid(n.trees = 700, interaction.depth = 5,
        shrinkage = 0.05, n.minobsinnode = 10)), xgbTree = caretModelSpec(method = "xgbTree",
      tuneGrid = expand.grid(nrounds = 2500, max_depth = 6,
        min_child_weight = 1.41, eta = 0.01, gamma = 0.0468,
        subsample = 0.769, colsample_bytree = 0.283))))

  greedy_ensemble <- caretEnsemble(modellist, metric = "RMSE",
    trControl = trainControl(number = 25))

  return(greedy_ensemble)
}
```

```
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1         0.1539             nan    0.0500    0.0122
##      2         0.1428             nan    0.0500    0.0104
```

##	3	0.1332	nan	0.0500	0.0090
##	4	0.1245	nan	0.0500	0.0084
##	5	0.1160	nan	0.0500	0.0073
##	6	0.1082	nan	0.0500	0.0072
##	7	0.1015	nan	0.0500	0.0070
##	8	0.0948	nan	0.0500	0.0064
##	9	0.0888	nan	0.0500	0.0056
##	10	0.0833	nan	0.0500	0.0054
##	20	0.0479	nan	0.0500	0.0022
##	40	0.0226	nan	0.0500	0.0006
##	60	0.0150	nan	0.0500	0.0002
##	80	0.0117	nan	0.0500	0.0000
##	100	0.0100	nan	0.0500	0.0001
##	120	0.0087	nan	0.0500	-0.0000
##	140	0.0077	nan	0.0500	0.0000
##	160	0.0070	nan	0.0500	-0.0000
##	180	0.0065	nan	0.0500	-0.0000
##	200	0.0059	nan	0.0500	-0.0000
##	220	0.0055	nan	0.0500	-0.0000
##	240	0.0052	nan	0.0500	-0.0000
##	260	0.0048	nan	0.0500	-0.0000
##	280	0.0045	nan	0.0500	-0.0000
##	300	0.0042	nan	0.0500	-0.0000
##	320	0.0040	nan	0.0500	-0.0000
##	340	0.0037	nan	0.0500	-0.0000
##	360	0.0035	nan	0.0500	-0.0000
##	380	0.0033	nan	0.0500	-0.0000
##	400	0.0032	nan	0.0500	-0.0000
##	420	0.0030	nan	0.0500	-0.0000
##	440	0.0028	nan	0.0500	-0.0000
##	460	0.0027	nan	0.0500	-0.0000
##	480	0.0025	nan	0.0500	-0.0000
##	500	0.0024	nan	0.0500	-0.0000
##	520	0.0023	nan	0.0500	-0.0000
##	540	0.0022	nan	0.0500	-0.0000
##	560	0.0021	nan	0.0500	-0.0000
##	580	0.0020	nan	0.0500	-0.0000
##	600	0.0019	nan	0.0500	-0.0000
##	620	0.0018	nan	0.0500	-0.0000
##	640	0.0017	nan	0.0500	-0.0000
##	660	0.0016	nan	0.0500	-0.0000
##	680	0.0016	nan	0.0500	-0.0000
##	700	0.0015	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1423	nan	0.0500	0.0109
##	2	0.1320	nan	0.0500	0.0100
##	3	0.1229	nan	0.0500	0.0082
##	4	0.1142	nan	0.0500	0.0088
##	5	0.1068	nan	0.0500	0.0075
##	6	0.1001	nan	0.0500	0.0067
##	7	0.0936	nan	0.0500	0.0062
##	8	0.0877	nan	0.0500	0.0055
##	9	0.0824	nan	0.0500	0.0053

##	10	0.0776	nan	0.0500	0.0047
##	20	0.0458	nan	0.0500	0.0018
##	40	0.0221	nan	0.0500	0.0005
##	60	0.0147	nan	0.0500	0.0001
##	80	0.0114	nan	0.0500	0.0001
##	100	0.0096	nan	0.0500	0.0000
##	120	0.0084	nan	0.0500	0.0000
##	140	0.0074	nan	0.0500	-0.0000
##	160	0.0068	nan	0.0500	0.0000
##	180	0.0062	nan	0.0500	-0.0000
##	200	0.0058	nan	0.0500	-0.0000
##	220	0.0053	nan	0.0500	-0.0000
##	240	0.0049	nan	0.0500	-0.0000
##	260	0.0046	nan	0.0500	-0.0000
##	280	0.0043	nan	0.0500	-0.0000
##	300	0.0040	nan	0.0500	-0.0000
##	320	0.0037	nan	0.0500	-0.0000
##	340	0.0035	nan	0.0500	0.0000
##	360	0.0033	nan	0.0500	-0.0000
##	380	0.0031	nan	0.0500	0.0000
##	400	0.0029	nan	0.0500	-0.0000
##	420	0.0027	nan	0.0500	-0.0000
##	440	0.0025	nan	0.0500	-0.0000
##	460	0.0024	nan	0.0500	0.0000
##	480	0.0023	nan	0.0500	-0.0000
##	500	0.0022	nan	0.0500	-0.0000
##	520	0.0020	nan	0.0500	-0.0000
##	540	0.0019	nan	0.0500	-0.0000
##	560	0.0018	nan	0.0500	-0.0000
##	580	0.0017	nan	0.0500	-0.0000
##	600	0.0017	nan	0.0500	-0.0000
##	620	0.0016	nan	0.0500	-0.0000
##	640	0.0015	nan	0.0500	-0.0000
##	660	0.0014	nan	0.0500	-0.0000
##	680	0.0013	nan	0.0500	-0.0000
##	700	0.0013	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1505	nan	0.0500	0.0128
##	2	0.1399	nan	0.0500	0.0100
##	3	0.1305	nan	0.0500	0.0087
##	4	0.1218	nan	0.0500	0.0092
##	5	0.1136	nan	0.0500	0.0078
##	6	0.1060	nan	0.0500	0.0075
##	7	0.0986	nan	0.0500	0.0070
##	8	0.0924	nan	0.0500	0.0059
##	9	0.0867	nan	0.0500	0.0059
##	10	0.0815	nan	0.0500	0.0053
##	20	0.0475	nan	0.0500	0.0024
##	40	0.0216	nan	0.0500	0.0006
##	60	0.0138	nan	0.0500	0.0002
##	80	0.0105	nan	0.0500	0.0000
##	100	0.0088	nan	0.0500	0.0000
##	120	0.0076	nan	0.0500	0.0000

##	140	0.0067	nan	0.0500	0.0000
##	160	0.0060	nan	0.0500	-0.0000
##	180	0.0055	nan	0.0500	0.0000
##	200	0.0050	nan	0.0500	-0.0000
##	220	0.0046	nan	0.0500	-0.0000
##	240	0.0043	nan	0.0500	-0.0000
##	260	0.0040	nan	0.0500	0.0000
##	280	0.0037	nan	0.0500	0.0000
##	300	0.0034	nan	0.0500	-0.0000
##	320	0.0032	nan	0.0500	-0.0000
##	340	0.0030	nan	0.0500	-0.0000
##	360	0.0028	nan	0.0500	-0.0000
##	380	0.0026	nan	0.0500	-0.0000
##	400	0.0025	nan	0.0500	-0.0000
##	420	0.0023	nan	0.0500	-0.0000
##	440	0.0022	nan	0.0500	-0.0000
##	460	0.0021	nan	0.0500	-0.0000
##	480	0.0020	nan	0.0500	-0.0000
##	500	0.0019	nan	0.0500	-0.0000
##	520	0.0018	nan	0.0500	-0.0000
##	540	0.0017	nan	0.0500	-0.0000
##	560	0.0016	nan	0.0500	-0.0000
##	580	0.0015	nan	0.0500	-0.0000
##	600	0.0015	nan	0.0500	-0.0000
##	620	0.0014	nan	0.0500	-0.0000
##	640	0.0013	nan	0.0500	-0.0000
##	660	0.0013	nan	0.0500	-0.0000
##	680	0.0012	nan	0.0500	-0.0000
##	700	0.0012	nan	0.0500	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve	
##	1	0.1487	nan	0.0500	0.0108
##	2	0.1379	nan	0.0500	0.0105
##	3	0.1280	nan	0.0500	0.0097
##	4	0.1192	nan	0.0500	0.0081
##	5	0.1113	nan	0.0500	0.0080
##	6	0.1039	nan	0.0500	0.0071
##	7	0.0972	nan	0.0500	0.0061
##	8	0.0908	nan	0.0500	0.0060
##	9	0.0852	nan	0.0500	0.0054
##	10	0.0800	nan	0.0500	0.0049
##	20	0.0462	nan	0.0500	0.0020
##	40	0.0210	nan	0.0500	0.0004
##	60	0.0135	nan	0.0500	0.0002
##	80	0.0103	nan	0.0500	0.0001
##	100	0.0086	nan	0.0500	0.0000
##	120	0.0075	nan	0.0500	-0.0000
##	140	0.0067	nan	0.0500	-0.0000
##	160	0.0060	nan	0.0500	0.0000
##	180	0.0055	nan	0.0500	-0.0000
##	200	0.0050	nan	0.0500	-0.0000
##	220	0.0046	nan	0.0500	-0.0000

##	240	0.0043	nan	0.0500	-0.0000
##	260	0.0040	nan	0.0500	-0.0000
##	280	0.0037	nan	0.0500	-0.0000
##	300	0.0035	nan	0.0500	-0.0000
##	320	0.0032	nan	0.0500	-0.0000
##	340	0.0031	nan	0.0500	-0.0000
##	360	0.0028	nan	0.0500	-0.0000
##	380	0.0027	nan	0.0500	-0.0000
##	400	0.0025	nan	0.0500	0.0000
##	420	0.0023	nan	0.0500	-0.0000
##	440	0.0022	nan	0.0500	-0.0000
##	460	0.0021	nan	0.0500	-0.0000
##	480	0.0020	nan	0.0500	-0.0000
##	500	0.0019	nan	0.0500	-0.0000
##	520	0.0018	nan	0.0500	-0.0000
##	540	0.0017	nan	0.0500	-0.0000
##	560	0.0016	nan	0.0500	-0.0000
##	580	0.0015	nan	0.0500	-0.0000
##	600	0.0014	nan	0.0500	-0.0000
##	620	0.0013	nan	0.0500	-0.0000
##	640	0.0013	nan	0.0500	-0.0000
##	660	0.0012	nan	0.0500	-0.0000
##	680	0.0012	nan	0.0500	-0.0000
##	700	0.0011	nan	0.0500	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve	
##	1	0.1507	nan	0.0500	0.0122
##	2	0.1406	nan	0.0500	0.0101
##	3	0.1311	nan	0.0500	0.0097
##	4	0.1227	nan	0.0500	0.0086
##	5	0.1136	nan	0.0500	0.0076
##	6	0.1062	nan	0.0500	0.0073
##	7	0.0992	nan	0.0500	0.0065
##	8	0.0926	nan	0.0500	0.0062
##	9	0.0868	nan	0.0500	0.0055
##	10	0.0811	nan	0.0500	0.0057
##	20	0.0453	nan	0.0500	0.0019
##	40	0.0207	nan	0.0500	0.0005
##	60	0.0133	nan	0.0500	0.0002
##	80	0.0102	nan	0.0500	0.0000
##	100	0.0084	nan	0.0500	0.0001
##	120	0.0074	nan	0.0500	-0.0000
##	140	0.0065	nan	0.0500	-0.0000
##	160	0.0060	nan	0.0500	-0.0000
##	180	0.0055	nan	0.0500	-0.0000
##	200	0.0051	nan	0.0500	-0.0000
##	220	0.0047	nan	0.0500	-0.0000
##	240	0.0044	nan	0.0500	0.0000
##	260	0.0042	nan	0.0500	-0.0000
##	280	0.0039	nan	0.0500	-0.0000
##	300	0.0037	nan	0.0500	-0.0000
##	320	0.0035	nan	0.0500	-0.0000



##	340	0.0033	nan	0.0500	-0.0000
##	360	0.0031	nan	0.0500	-0.0000
##	380	0.0029	nan	0.0500	-0.0000
##	400	0.0028	nan	0.0500	-0.0000
##	420	0.0026	nan	0.0500	-0.0000
##	440	0.0025	nan	0.0500	-0.0000
##	460	0.0023	nan	0.0500	-0.0000
##	480	0.0022	nan	0.0500	-0.0000
##	500	0.0021	nan	0.0500	-0.0000
##	520	0.0020	nan	0.0500	-0.0000
##	540	0.0019	nan	0.0500	-0.0000
##	560	0.0018	nan	0.0500	-0.0000
##	580	0.0018	nan	0.0500	-0.0000
##	600	0.0017	nan	0.0500	-0.0000
##	620	0.0016	nan	0.0500	-0.0000
##	640	0.0015	nan	0.0500	-0.0000
##	660	0.0015	nan	0.0500	-0.0000
##	680	0.0014	nan	0.0500	-0.0000
##	700	0.0013	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1501	nan	0.0500	0.0109
##	2	0.1396	nan	0.0500	0.0113
##	3	0.1299	nan	0.0500	0.0095
##	4	0.1214	nan	0.0500	0.0080
##	5	0.1132	nan	0.0500	0.0080
##	6	0.1057	nan	0.0500	0.0070
##	7	0.0987	nan	0.0500	0.0071
##	8	0.0922	nan	0.0500	0.0058
##	9	0.0862	nan	0.0500	0.0054
##	10	0.0812	nan	0.0500	0.0052
##	20	0.0471	nan	0.0500	0.0021
##	40	0.0226	nan	0.0500	0.0004
##	60	0.0150	nan	0.0500	0.0001
##	80	0.0117	nan	0.0500	0.0000
##	100	0.0098	nan	0.0500	0.0000
##	120	0.0087	nan	0.0500	0.0000
##	140	0.0078	nan	0.0500	-0.0000
##	160	0.0070	nan	0.0500	0.0000
##	180	0.0065	nan	0.0500	-0.0000
##	200	0.0060	nan	0.0500	-0.0000
##	220	0.0056	nan	0.0500	-0.0000
##	240	0.0052	nan	0.0500	-0.0000
##	260	0.0048	nan	0.0500	-0.0000
##	280	0.0045	nan	0.0500	-0.0000
##	300	0.0042	nan	0.0500	-0.0000
##	320	0.0040	nan	0.0500	-0.0000
##	340	0.0038	nan	0.0500	-0.0000
##	360	0.0036	nan	0.0500	-0.0000
##	380	0.0034	nan	0.0500	-0.0000
##	400	0.0032	nan	0.0500	-0.0000
##	420	0.0030	nan	0.0500	-0.0000
##	440	0.0028	nan	0.0500	-0.0000
##	460	0.0027	nan	0.0500	-0.0000

##	480	0.0025	nan	0.0500	-0.0000
##	500	0.0024	nan	0.0500	0.0000
##	520	0.0023	nan	0.0500	-0.0000
##	540	0.0022	nan	0.0500	-0.0000
##	560	0.0021	nan	0.0500	-0.0000
##	580	0.0020	nan	0.0500	-0.0000
##	600	0.0019	nan	0.0500	-0.0000
##	620	0.0018	nan	0.0500	-0.0000
##	640	0.0017	nan	0.0500	-0.0000
##	660	0.0016	nan	0.0500	-0.0000
##	680	0.0016	nan	0.0500	-0.0000
##	700	0.0015	nan	0.0500	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1516	nan	0.0500	0.0110
##	2	0.1411	nan	0.0500	0.0103
##	3	0.1316	nan	0.0500	0.0087
##	4	0.1231	nan	0.0500	0.0087
##	5	0.1154	nan	0.0500	0.0078
##	6	0.1078	nan	0.0500	0.0074
##	7	0.1009	nan	0.0500	0.0064
##	8	0.0944	nan	0.0500	0.0061
##	9	0.0886	nan	0.0500	0.0054
##	10	0.0833	nan	0.0500	0.0052
##	20	0.0483	nan	0.0500	0.0023
##	40	0.0228	nan	0.0500	0.0005
##	60	0.0148	nan	0.0500	0.0001
##	80	0.0115	nan	0.0500	0.0000
##	100	0.0095	nan	0.0500	0.0000
##	120	0.0083	nan	0.0500	0.0000
##	140	0.0074	nan	0.0500	0.0000
##	160	0.0067	nan	0.0500	0.0000
##	180	0.0061	nan	0.0500	-0.0000
##	200	0.0056	nan	0.0500	-0.0000
##	220	0.0052	nan	0.0500	-0.0000
##	240	0.0048	nan	0.0500	-0.0000
##	260	0.0045	nan	0.0500	-0.0000
##	280	0.0042	nan	0.0500	0.0000
##	300	0.0039	nan	0.0500	-0.0000
##	320	0.0037	nan	0.0500	-0.0000
##	340	0.0035	nan	0.0500	0.0000
##	360	0.0033	nan	0.0500	-0.0000
##	380	0.0031	nan	0.0500	-0.0000
##	400	0.0029	nan	0.0500	-0.0000
##	420	0.0028	nan	0.0500	-0.0000
##	440	0.0026	nan	0.0500	-0.0000
##	460	0.0025	nan	0.0500	-0.0000
##	480	0.0023	nan	0.0500	-0.0000
##	500	0.0022	nan	0.0500	-0.0000
##	520	0.0021	nan	0.0500	-0.0000
##	540	0.0020	nan	0.0500	-0.0000
##	560	0.0019	nan	0.0500	-0.0000

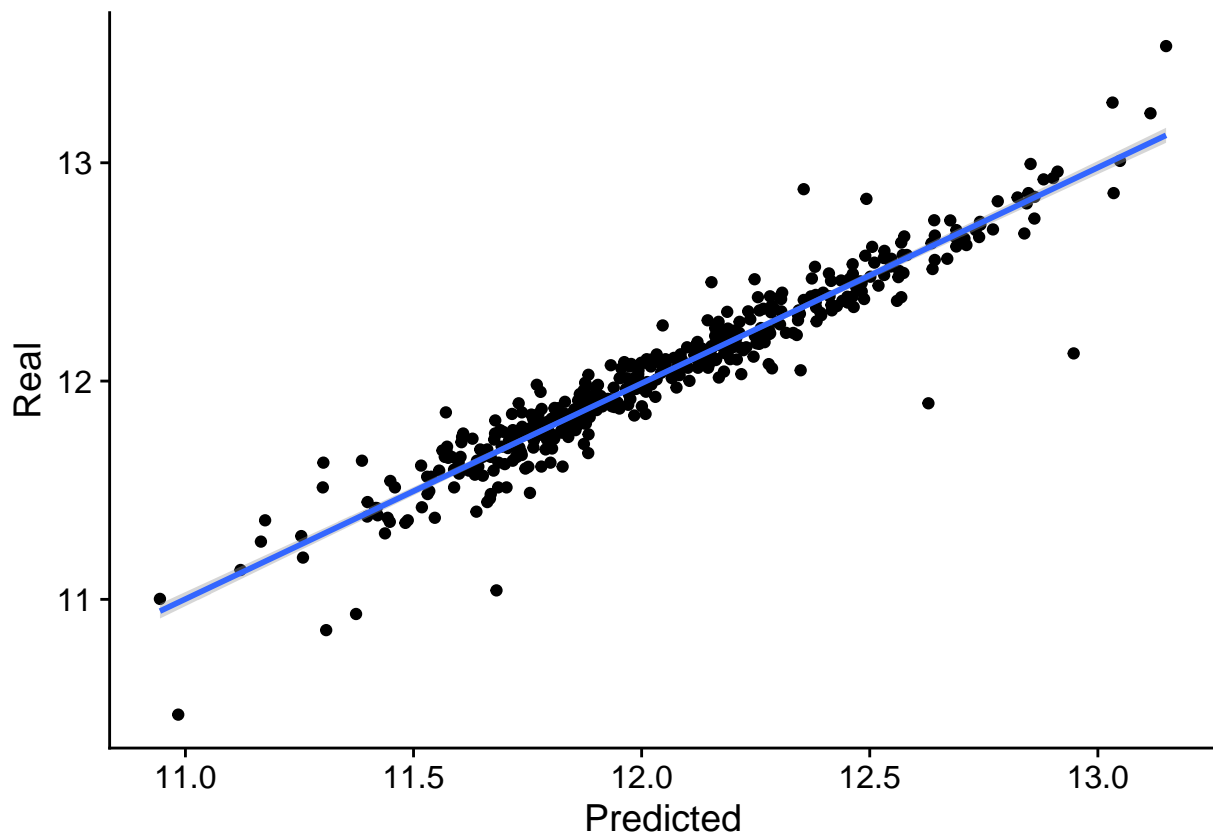
##	580	0.0018	nan	0.0500	-0.0000
##	600	0.0017	nan	0.0500	-0.0000
##	620	0.0016	nan	0.0500	-0.0000
##	640	0.0016	nan	0.0500	-0.0000
##	660	0.0015	nan	0.0500	-0.0000
##	680	0.0014	nan	0.0500	-0.0000
##	700	0.0013	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1506	nan	0.0500	0.0110
##	2	0.1407	nan	0.0500	0.0097
##	3	0.1308	nan	0.0500	0.0092
##	4	0.1222	nan	0.0500	0.0085
##	5	0.1144	nan	0.0500	0.0075
##	6	0.1071	nan	0.0500	0.0066
##	7	0.1002	nan	0.0500	0.0064
##	8	0.0939	nan	0.0500	0.0062
##	9	0.0885	nan	0.0500	0.0049
##	10	0.0831	nan	0.0500	0.0047
##	20	0.0482	nan	0.0500	0.0021
##	40	0.0239	nan	0.0500	0.0005
##	60	0.0168	nan	0.0500	0.0002
##	80	0.0136	nan	0.0500	0.0000
##	100	0.0119	nan	0.0500	-0.0000
##	120	0.0106	nan	0.0500	0.0000
##	140	0.0098	nan	0.0500	-0.0000
##	160	0.0091	nan	0.0500	-0.0000
##	180	0.0086	nan	0.0500	-0.0000
##	200	0.0081	nan	0.0500	-0.0000
##	220	0.0077	nan	0.0500	-0.0000
##	240	0.0073	nan	0.0500	-0.0000
##	260	0.0070	nan	0.0500	-0.0000
##	280	0.0066	nan	0.0500	-0.0000
##	300	0.0064	nan	0.0500	-0.0000
##	320	0.0061	nan	0.0500	-0.0000
##	340	0.0058	nan	0.0500	-0.0000
##	360	0.0056	nan	0.0500	-0.0000
##	380	0.0054	nan	0.0500	-0.0000
##	400	0.0052	nan	0.0500	-0.0000
##	420	0.0050	nan	0.0500	-0.0000
##	440	0.0048	nan	0.0500	-0.0000
##	460	0.0046	nan	0.0500	-0.0000
##	480	0.0044	nan	0.0500	-0.0000
##	500	0.0043	nan	0.0500	-0.0000
##	520	0.0041	nan	0.0500	-0.0000
##	540	0.0039	nan	0.0500	-0.0000
##	560	0.0038	nan	0.0500	-0.0000
##	580	0.0037	nan	0.0500	-0.0000
##	600	0.0035	nan	0.0500	-0.0000
##	620	0.0034	nan	0.0500	-0.0000
##	640	0.0033	nan	0.0500	-0.0000
##	660	0.0032	nan	0.0500	-0.0000
##	680	0.0031	nan	0.0500	-0.0000
##	700	0.0029	nan	0.0500	-0.0000

```
model.ensemble # 0.130408 # 0.1307172
```

```
## A glm ensemble of 2 base models: gbm, xgbTree
##
## Ensemble results:
## Generalized Linear Model
##
## 2641 samples
## 2 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 2641, 2641, 2641, 2641, 2641, 2641, ...
## Resampling results:
##
## RMSE      Rsquared    MAE
## 0.1267544 0.8998718 0.08639417
```

```
predictAndEvaluate(model.ensemble, train.processed.partition.validation) # 0.1217003 # 0.1296369
```

```
## Warning: Ignoring unknown parameters: method
```



```
## [1] 0.1181355
```

## Full train

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1541	nan	0.0500	0.0128
##	2	0.1435	nan	0.0500	0.0105
##	3	0.1337	nan	0.0500	0.0096
##	4	0.1248	nan	0.0500	0.0083
##	5	0.1167	nan	0.0500	0.0080
##	6	0.1093	nan	0.0500	0.0067
##	7	0.1023	nan	0.0500	0.0068
##	8	0.0958	nan	0.0500	0.0061
##	9	0.0899	nan	0.0500	0.0059
##	10	0.0843	nan	0.0500	0.0055
##	20	0.0477	nan	0.0500	0.0024
##	40	0.0225	nan	0.0500	0.0006
##	60	0.0149	nan	0.0500	0.0002
##	80	0.0117	nan	0.0500	0.0001
##	100	0.0099	nan	0.0500	0.0000
##	120	0.0087	nan	0.0500	-0.0000
##	140	0.0080	nan	0.0500	-0.0000
##	160	0.0074	nan	0.0500	-0.0000
##	180	0.0069	nan	0.0500	-0.0000
##	200	0.0065	nan	0.0500	-0.0000
##	220	0.0061	nan	0.0500	0.0000
##	240	0.0056	nan	0.0500	0.0000
##	260	0.0053	nan	0.0500	-0.0000
##	280	0.0050	nan	0.0500	-0.0000
##	300	0.0047	nan	0.0500	-0.0000
##	320	0.0045	nan	0.0500	-0.0000
##	340	0.0043	nan	0.0500	-0.0000
##	360	0.0041	nan	0.0500	-0.0000
##	380	0.0039	nan	0.0500	-0.0000
##	400	0.0037	nan	0.0500	-0.0000
##	420	0.0036	nan	0.0500	-0.0000
##	440	0.0034	nan	0.0500	-0.0000
##	460	0.0033	nan	0.0500	-0.0000
##	480	0.0031	nan	0.0500	-0.0000
##	500	0.0030	nan	0.0500	-0.0000
##	520	0.0029	nan	0.0500	-0.0000
##	540	0.0028	nan	0.0500	-0.0000
##	560	0.0026	nan	0.0500	-0.0000
##	580	0.0025	nan	0.0500	-0.0000
##	600	0.0024	nan	0.0500	-0.0000
##	620	0.0023	nan	0.0500	-0.0000
##	640	0.0022	nan	0.0500	-0.0000
##	660	0.0022	nan	0.0500	-0.0000
##	680	0.0021	nan	0.0500	0.0000
##	700	0.0020	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1487	nan	0.0500	0.0113
##	2	0.1382	nan	0.0500	0.0102
##	3	0.1287	nan	0.0500	0.0100
##	4	0.1201	nan	0.0500	0.0081

##	5	0.1124	nan	0.0500	0.0077
##	6	0.1052	nan	0.0500	0.0069
##	7	0.0984	nan	0.0500	0.0066
##	8	0.0924	nan	0.0500	0.0055
##	9	0.0868	nan	0.0500	0.0052
##	10	0.0815	nan	0.0500	0.0047
##	20	0.0478	nan	0.0500	0.0022
##	40	0.0229	nan	0.0500	0.0005
##	60	0.0151	nan	0.0500	0.0002
##	80	0.0119	nan	0.0500	0.0001
##	100	0.0101	nan	0.0500	0.0000
##	120	0.0091	nan	0.0500	-0.0000
##	140	0.0083	nan	0.0500	0.0000
##	160	0.0077	nan	0.0500	0.0000
##	180	0.0071	nan	0.0500	-0.0000
##	200	0.0066	nan	0.0500	-0.0000
##	220	0.0062	nan	0.0500	-0.0000
##	240	0.0058	nan	0.0500	-0.0000
##	260	0.0055	nan	0.0500	-0.0000
##	280	0.0052	nan	0.0500	-0.0000
##	300	0.0049	nan	0.0500	-0.0000
##	320	0.0047	nan	0.0500	-0.0000
##	340	0.0044	nan	0.0500	-0.0000
##	360	0.0042	nan	0.0500	-0.0000
##	380	0.0040	nan	0.0500	-0.0000
##	400	0.0038	nan	0.0500	-0.0000
##	420	0.0036	nan	0.0500	0.0000
##	440	0.0034	nan	0.0500	-0.0000
##	460	0.0033	nan	0.0500	-0.0000
##	480	0.0032	nan	0.0500	-0.0000
##	500	0.0030	nan	0.0500	-0.0000
##	520	0.0029	nan	0.0500	-0.0000
##	540	0.0028	nan	0.0500	-0.0000
##	560	0.0027	nan	0.0500	-0.0000
##	580	0.0026	nan	0.0500	-0.0000
##	600	0.0025	nan	0.0500	-0.0000
##	620	0.0024	nan	0.0500	-0.0000
##	640	0.0023	nan	0.0500	-0.0000
##	660	0.0022	nan	0.0500	-0.0000
##	680	0.0021	nan	0.0500	-0.0000
##	700	0.0020	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1574	nan	0.0500	0.0121
##	2	0.1463	nan	0.0500	0.0111
##	3	0.1359	nan	0.0500	0.0095
##	4	0.1268	nan	0.0500	0.0090
##	5	0.1184	nan	0.0500	0.0080
##	6	0.1102	nan	0.0500	0.0069
##	7	0.1029	nan	0.0500	0.0074
##	8	0.0966	nan	0.0500	0.0059
##	9	0.0903	nan	0.0500	0.0059
##	10	0.0852	nan	0.0500	0.0049
##	20	0.0492	nan	0.0500	0.0023

##	40	0.0241	nan	0.0500	0.0005
##	60	0.0161	nan	0.0500	0.0002
##	80	0.0128	nan	0.0500	0.0001
##	100	0.0109	nan	0.0500	-0.0000
##	120	0.0097	nan	0.0500	0.0000
##	140	0.0089	nan	0.0500	0.0000
##	160	0.0081	nan	0.0500	0.0000
##	180	0.0075	nan	0.0500	0.0000
##	200	0.0070	nan	0.0500	-0.0000
##	220	0.0066	nan	0.0500	0.0000
##	240	0.0062	nan	0.0500	-0.0000
##	260	0.0059	nan	0.0500	-0.0000
##	280	0.0056	nan	0.0500	-0.0000
##	300	0.0053	nan	0.0500	-0.0000
##	320	0.0050	nan	0.0500	-0.0000
##	340	0.0047	nan	0.0500	-0.0000
##	360	0.0045	nan	0.0500	-0.0000
##	380	0.0043	nan	0.0500	-0.0000
##	400	0.0041	nan	0.0500	-0.0000
##	420	0.0039	nan	0.0500	-0.0000
##	440	0.0038	nan	0.0500	-0.0000
##	460	0.0036	nan	0.0500	-0.0000
##	480	0.0035	nan	0.0500	-0.0000
##	500	0.0033	nan	0.0500	-0.0000
##	520	0.0032	nan	0.0500	-0.0000
##	540	0.0031	nan	0.0500	-0.0000
##	560	0.0030	nan	0.0500	-0.0000
##	580	0.0029	nan	0.0500	-0.0000
##	600	0.0027	nan	0.0500	-0.0000
##	620	0.0026	nan	0.0500	-0.0000
##	640	0.0025	nan	0.0500	-0.0000
##	660	0.0025	nan	0.0500	-0.0000
##	680	0.0024	nan	0.0500	-0.0000
##	700	0.0023	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1627	nan	0.0500	0.0119
##	2	0.1514	nan	0.0500	0.0112
##	3	0.1412	nan	0.0500	0.0101
##	4	0.1319	nan	0.0500	0.0092
##	5	0.1234	nan	0.0500	0.0081
##	6	0.1157	nan	0.0500	0.0071
##	7	0.1083	nan	0.0500	0.0071
##	8	0.1015	nan	0.0500	0.0069
##	9	0.0954	nan	0.0500	0.0060
##	10	0.0897	nan	0.0500	0.0055
##	20	0.0517	nan	0.0500	0.0023
##	40	0.0247	nan	0.0500	0.0007
##	60	0.0163	nan	0.0500	0.0002
##	80	0.0126	nan	0.0500	0.0001
##	100	0.0106	nan	0.0500	-0.0000
##	120	0.0093	nan	0.0500	0.0000
##	140	0.0084	nan	0.0500	0.0000
##	160	0.0076	nan	0.0500	-0.0000

##	180	0.0070	nan	0.0500	-0.0000
##	200	0.0064	nan	0.0500	-0.0000
##	220	0.0060	nan	0.0500	-0.0000
##	240	0.0056	nan	0.0500	-0.0000
##	260	0.0053	nan	0.0500	-0.0000
##	280	0.0050	nan	0.0500	-0.0000
##	300	0.0047	nan	0.0500	-0.0000
##	320	0.0045	nan	0.0500	-0.0000
##	340	0.0042	nan	0.0500	-0.0000
##	360	0.0040	nan	0.0500	0.0000
##	380	0.0038	nan	0.0500	-0.0000
##	400	0.0037	nan	0.0500	0.0000
##	420	0.0035	nan	0.0500	-0.0000
##	440	0.0033	nan	0.0500	-0.0000
##	460	0.0032	nan	0.0500	-0.0000
##	480	0.0031	nan	0.0500	-0.0000
##	500	0.0029	nan	0.0500	-0.0000
##	520	0.0028	nan	0.0500	-0.0000
##	540	0.0027	nan	0.0500	-0.0000
##	560	0.0026	nan	0.0500	-0.0000
##	580	0.0025	nan	0.0500	-0.0000
##	600	0.0024	nan	0.0500	-0.0000
##	620	0.0023	nan	0.0500	-0.0000
##	640	0.0022	nan	0.0500	-0.0000
##	660	0.0021	nan	0.0500	-0.0000
##	680	0.0021	nan	0.0500	-0.0000
##	700	0.0020	nan	0.0500	-0.0000

## Warning in (function (x, y, offset = NULL, misc = NULL, distribution =  
## "bernoulli", : variable 8: Utilities has no variation.

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1549	nan	0.0500	0.0106
##	2	0.1438	nan	0.0500	0.0103
##	3	0.1341	nan	0.0500	0.0094
##	4	0.1251	nan	0.0500	0.0091
##	5	0.1169	nan	0.0500	0.0081
##	6	0.1098	nan	0.0500	0.0073
##	7	0.1032	nan	0.0500	0.0067
##	8	0.0967	nan	0.0500	0.0066
##	9	0.0907	nan	0.0500	0.0060
##	10	0.0853	nan	0.0500	0.0053
##	20	0.0495	nan	0.0500	0.0023
##	40	0.0243	nan	0.0500	0.0006
##	60	0.0165	nan	0.0500	0.0002
##	80	0.0130	nan	0.0500	0.0001
##	100	0.0111	nan	0.0500	0.0000
##	120	0.0098	nan	0.0500	0.0000
##	140	0.0088	nan	0.0500	0.0000
##	160	0.0080	nan	0.0500	0.0000
##	180	0.0074	nan	0.0500	-0.0000
##	200	0.0068	nan	0.0500	-0.0000
##	220	0.0064	nan	0.0500	-0.0000
##	240	0.0060	nan	0.0500	-0.0000
##	260	0.0056	nan	0.0500	-0.0000



##	280	0.0053	nan	0.0500	-0.0000
##	300	0.0050	nan	0.0500	-0.0000
##	320	0.0047	nan	0.0500	-0.0000
##	340	0.0044	nan	0.0500	-0.0000
##	360	0.0042	nan	0.0500	-0.0000
##	380	0.0040	nan	0.0500	-0.0000
##	400	0.0038	nan	0.0500	0.0000
##	420	0.0037	nan	0.0500	-0.0000
##	440	0.0035	nan	0.0500	-0.0000
##	460	0.0033	nan	0.0500	-0.0000
##	480	0.0032	nan	0.0500	-0.0000
##	500	0.0031	nan	0.0500	-0.0000
##	520	0.0030	nan	0.0500	-0.0000
##	540	0.0029	nan	0.0500	-0.0000
##	560	0.0028	nan	0.0500	0.0000
##	580	0.0027	nan	0.0500	-0.0000
##	600	0.0026	nan	0.0500	-0.0000
##	620	0.0025	nan	0.0500	-0.0000
##	640	0.0024	nan	0.0500	-0.0000
##	660	0.0023	nan	0.0500	-0.0000
##	680	0.0022	nan	0.0500	-0.0000
##	700	0.0021	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1427	nan	0.0500	0.0109
##	2	0.1325	nan	0.0500	0.0098
##	3	0.1233	nan	0.0500	0.0094
##	4	0.1152	nan	0.0500	0.0077
##	5	0.1075	nan	0.0500	0.0073
##	6	0.1005	nan	0.0500	0.0074
##	7	0.0942	nan	0.0500	0.0062
##	8	0.0882	nan	0.0500	0.0051
##	9	0.0825	nan	0.0500	0.0053
##	10	0.0774	nan	0.0500	0.0049
##	20	0.0448	nan	0.0500	0.0021
##	40	0.0210	nan	0.0500	0.0005
##	60	0.0137	nan	0.0500	0.0002
##	80	0.0106	nan	0.0500	0.0001
##	100	0.0090	nan	0.0500	0.0000
##	120	0.0079	nan	0.0500	0.0000
##	140	0.0072	nan	0.0500	0.0000
##	160	0.0066	nan	0.0500	0.0000
##	180	0.0061	nan	0.0500	-0.0000
##	200	0.0057	nan	0.0500	-0.0000
##	220	0.0053	nan	0.0500	0.0000
##	240	0.0050	nan	0.0500	0.0000
##	260	0.0048	nan	0.0500	-0.0000
##	280	0.0045	nan	0.0500	-0.0000
##	300	0.0043	nan	0.0500	-0.0000
##	320	0.0041	nan	0.0500	-0.0000
##	340	0.0039	nan	0.0500	0.0000
##	360	0.0037	nan	0.0500	-0.0000
##	380	0.0036	nan	0.0500	-0.0000
##	400	0.0034	nan	0.0500	-0.0000

##	420	0.0033	nan	0.0500	-0.0000
##	440	0.0031	nan	0.0500	-0.0000
##	460	0.0030	nan	0.0500	-0.0000
##	480	0.0029	nan	0.0500	-0.0000
##	500	0.0028	nan	0.0500	-0.0000
##	520	0.0026	nan	0.0500	-0.0000
##	540	0.0025	nan	0.0500	-0.0000
##	560	0.0024	nan	0.0500	-0.0000
##	580	0.0023	nan	0.0500	-0.0000
##	600	0.0022	nan	0.0500	-0.0000
##	620	0.0022	nan	0.0500	-0.0000
##	640	0.0021	nan	0.0500	-0.0000
##	660	0.0020	nan	0.0500	-0.0000
##	680	0.0019	nan	0.0500	0.0000
##	700	0.0019	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1564	nan	0.0500	0.0119
##	2	0.1460	nan	0.0500	0.0107
##	3	0.1359	nan	0.0500	0.0107
##	4	0.1268	nan	0.0500	0.0091
##	5	0.1187	nan	0.0500	0.0077
##	6	0.1118	nan	0.0500	0.0069
##	7	0.1048	nan	0.0500	0.0063
##	8	0.0987	nan	0.0500	0.0061
##	9	0.0927	nan	0.0500	0.0061
##	10	0.0874	nan	0.0500	0.0051
##	20	0.0507	nan	0.0500	0.0027
##	40	0.0247	nan	0.0500	0.0005
##	60	0.0167	nan	0.0500	0.0002
##	80	0.0131	nan	0.0500	0.0001
##	100	0.0112	nan	0.0500	0.0000
##	120	0.0099	nan	0.0500	-0.0000
##	140	0.0089	nan	0.0500	0.0000
##	160	0.0081	nan	0.0500	-0.0000
##	180	0.0076	nan	0.0500	-0.0000
##	200	0.0070	nan	0.0500	-0.0000
##	220	0.0066	nan	0.0500	0.0000
##	240	0.0062	nan	0.0500	-0.0000
##	260	0.0058	nan	0.0500	0.0000
##	280	0.0055	nan	0.0500	-0.0000
##	300	0.0051	nan	0.0500	-0.0000
##	320	0.0049	nan	0.0500	-0.0000
##	340	0.0046	nan	0.0500	-0.0000
##	360	0.0044	nan	0.0500	-0.0000
##	380	0.0042	nan	0.0500	-0.0000
##	400	0.0039	nan	0.0500	-0.0000
##	420	0.0038	nan	0.0500	-0.0000
##	440	0.0036	nan	0.0500	0.0000
##	460	0.0034	nan	0.0500	-0.0000
##	480	0.0033	nan	0.0500	-0.0000
##	500	0.0031	nan	0.0500	-0.0000
##	520	0.0030	nan	0.0500	0.0000
##	540	0.0029	nan	0.0500	-0.0000

##	560	0.0028	nan	0.0500	-0.0000
##	580	0.0027	nan	0.0500	-0.0000
##	600	0.0026	nan	0.0500	-0.0000
##	620	0.0025	nan	0.0500	-0.0000
##	640	0.0024	nan	0.0500	-0.0000
##	660	0.0023	nan	0.0500	-0.0000
##	680	0.0022	nan	0.0500	-0.0000
##	700	0.0021	nan	0.0500	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1480	nan	0.0500	0.0115
##	2	0.1377	nan	0.0500	0.0096
##	3	0.1286	nan	0.0500	0.0087
##	4	0.1205	nan	0.0500	0.0085
##	5	0.1134	nan	0.0500	0.0066
##	6	0.1059	nan	0.0500	0.0069
##	7	0.0991	nan	0.0500	0.0070
##	8	0.0933	nan	0.0500	0.0057
##	9	0.0880	nan	0.0500	0.0050
##	10	0.0832	nan	0.0500	0.0047
##	20	0.0498	nan	0.0500	0.0020
##	40	0.0258	nan	0.0500	0.0005
##	60	0.0183	nan	0.0500	0.0001
##	80	0.0149	nan	0.0500	0.0001
##	100	0.0130	nan	0.0500	0.0000
##	120	0.0118	nan	0.0500	-0.0000
##	140	0.0109	nan	0.0500	-0.0000
##	160	0.0102	nan	0.0500	-0.0000
##	180	0.0096	nan	0.0500	-0.0000
##	200	0.0092	nan	0.0500	-0.0000
##	220	0.0088	nan	0.0500	-0.0000
##	240	0.0083	nan	0.0500	-0.0000
##	260	0.0080	nan	0.0500	-0.0000
##	280	0.0077	nan	0.0500	-0.0000
##	300	0.0075	nan	0.0500	-0.0000
##	320	0.0072	nan	0.0500	-0.0000
##	340	0.0069	nan	0.0500	-0.0000
##	360	0.0067	nan	0.0500	-0.0000
##	380	0.0065	nan	0.0500	-0.0000
##	400	0.0062	nan	0.0500	-0.0000
##	420	0.0060	nan	0.0500	-0.0000
##	440	0.0058	nan	0.0500	-0.0000
##	460	0.0056	nan	0.0500	-0.0000
##	480	0.0054	nan	0.0500	-0.0000
##	500	0.0053	nan	0.0500	-0.0000
##	520	0.0051	nan	0.0500	-0.0000
##	540	0.0050	nan	0.0500	-0.0000
##	560	0.0048	nan	0.0500	-0.0000
##	580	0.0047	nan	0.0500	-0.0000
##	600	0.0045	nan	0.0500	-0.0000
##	620	0.0044	nan	0.0500	-0.0000
##	640	0.0043	nan	0.0500	-0.0000
##	660	0.0042	nan	0.0500	-0.0000
##	680	0.0040	nan	0.0500	-0.0000

```
##      700      0.0039      nan      0.0500     -0.0000
model.full # 0.1261884 # 0.1345461 # 0.1254348

## A glm ensemble of 2 base models: gbm, xgbTree
##
## Ensemble results:
## Generalized Linear Model
##
## 3736 samples
##    2 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 3736, 3736, 3736, 3736, 3736, 3736, ...
## Resampling results:
##
##      RMSE      Rsquared    MAE
## 0.1254348 0.8993666 0.08295416
```

## Prediction and submit

```
predictions <- predict(model.full, newdata = test.processed)
prediction.table <- data.frame(Id = test$Id, SalePrice = exp(predictions))
write.csv(prediction.table, "prediction.csv", row.names = FALSE) # Kaggle: 0.12246
```