

In-Class 8

```
# load packages
library(tidyverse)
```

Load data

The data we will be working with contains information about the housing market in Ames, TX.

We need to load the following RData file, which contains a training and testing dataset.

```
# read in training and testing data
load('regression-data.RData')

# preview training data
glimpse(data_train)
```

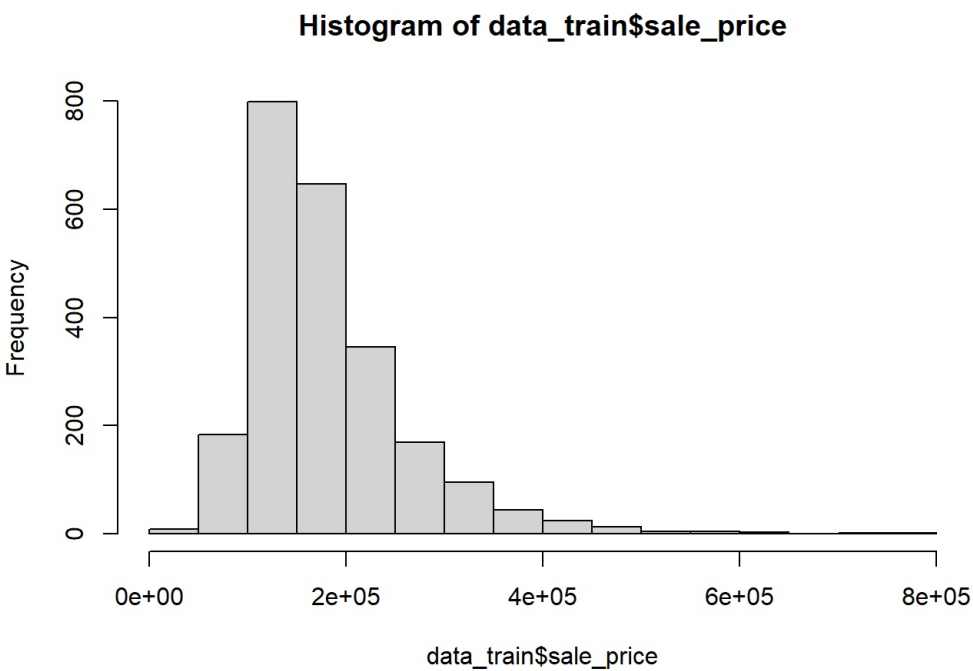
```
Rows: 2,344
Columns: 61
$ lot_frontage    <dbl> 46, 60, 0, 78, 74, 43, 0, 0, 80, 80, 100, 60, 21, 75, ...
$ lot_area        <int> 20544, 7200, 9555, 15600, 11988, 3182, 10464, 4426, 92...
$ year_built      <int> 1986, 1949, 1979, 1949, 1934, 2005, 1980, 2004, 1965, ...
$ year_remod_add  <int> 1991, 1950, 1979, 2005, 1995, 2006, 1980, 2004, 1965, ...
$ mas_vnr_area    <dbl> 123, 0, 0, 0, 0, 16, 130, 169, 0, 252, 0, 0, 0, 0, 0, ...
$ bsmt_fin_sf_1   <dbl> 7, 5, 5, 2, 4, 3, 3, 3, 6, 1, 3, 7, 3, 3, 1, 7, 7, 7, ...
$ bsmt_unf_sf     <dbl> 791, 0, 0, 248, 389, 1357, 138, 186, 244, 467, 172, 85...
$ total_bsmt_sf   <dbl> 791, 0, 0, 1067, 715, 1373, 988, 848, 1136, 1165, 924,...
$ first_flr_sf    <int> 1236, 1040, 1100, 986, 849, 1555, 1102, 848, 1136, 116...
$ second_flr_sf   <int> 857, 0, 1133, 537, 811, 0, 0, 0, 896, 0, 0, 546, 14...
$ gr_liv_area     <int> 2093, 1040, 2233, 1523, 1660, 1555, 1102, 848, 1136, 2...
$ bsmt_full_bath  <dbl> 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, ...
$ full_bath       <int> 2, 2, 2, 2, 1, 2, 1, 1, 1, 2, 1, 1, 1, 2, 2, 2, 2, 2, ...
$ half_bath       <int> 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, ...
$ bedroom_abv_gr  <int> 3, 2, 5, 3, 3, 2, 2, 1, 3, 4, 2, 2, 3, 4, 4, 4, 3, 3, ...
$ kitchen_abv_gr  <int> 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
$ tot_rms_abv_grd <int> 7, 6, 11, 7, 6, 7, 5, 3, 5, 8, 6, 5, 5, 11, 8, 8, 10, ...
$ fireplaces      <int> 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, ...
$ garage_cars     <dbl> 2, 2, 2, 1, 1, 2, 2, 2, 1, 2, 2, 2, 0, 2, 2, 2, 3, 3, ...
$ garage_area     <dbl> 542, 420, 579, 295, 240, 430, 582, 420, 384, 498, 528,...
$ wood_deck_sf    <int> 364, 0, 0, 0, 0, 143, 140, 160, 426, 0, 0, 0, 200, 208...
$ open_porch_sf   <int> 63, 0, 0, 0, 0, 20, 22, 0, 0, 77, 36, 0, 26, 364, 207,...
$ enclosed_porch  <int> 0, 0, 0, 81, 0, 0, 0, 0, 0, 0, 0, 0, 116, 0, 0, 0, 0, 0, ...
$ screen_porch    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 196, 0, 0, 0, 0, 224, 0, 0,...
$ sale_price      <int> 215000, 90000, 141000, 158000, 188700, 192500, 169000,...
$ longitude       <dbl> -93.63915, -93.60890, -93.67433, -93.64076, -93.64141,...
$ latitude        <dbl> 42.05602, 42.03584, 42.01917, 42.01494, 42.01844, 42.0...
$ ms_zoning       <fct> Residential_Low_Density, Residential_Low_Density, Resi...
$ street          <fct> Pave, Pave, Pave, Pave, Pave, Pave, Pave, Pave, Pave, ...
$ alley           <fct> No_Alley_Access, No_Alley_Access, No_Alley_Access, No_...
$ lot_shape       <fct> Slightly_Irregular, Regular, Slightly_Irregular, Regul...
$ land_contour    <fct> Lvl, Lvl, Lvl, Bnk, HLS, Lvl, Lvl, Lvl, Lvl, Lvl, Lvl,...
$ lot_config      <fct> CulDSac, Inside, CulDSac, Inside, Inside, Inside, FR3,...
$ land_slope      <fct> Gtl, Gtl, Gtl, Gtl, Mod, Gtl, Gtl, Gtl, Gtl, Gtl, Gtl,...
$ condition_1     <fct> Norm, Norm, Norm, Norm, Norm, Norm, Norm, Norm, Norm, ...
$ condition_2     <fct> Norm, Norm, Norm, Norm, Norm, Norm, Norm, Norm, Norm, ...
$ bldg_type       <fct> OneFam, Duplex, Duplex, OneFam, OneFam, TwnhsE, OneFam...
$ house_style     <fct> Two_Story, One_Story, Two_Story, One_and_Half_Fin, Two...
$ overall_cond    <fct> Above_Average, Average, Above_Average, Good, Good, Ave...
$ roof_style      <fct> Gable, Gable, Gable, Gable, Hip, Gable, Gable, Gable, ...
$ roof_matl       <fct> CompShg, CompShg, CompShg, CompShg, CompShg, CompShg, ...
$ mas_vnr_type    <fct> BrkFace, None, None, None, None, BrkFace, BrkFace, Brk...
$ exter_cond      <fct> Good, Typical, Typical, Typical, Typical, Typical, Typ...
$ foundation      <fct> CBlock, Slab, Slab, BrkTil, CBlock, PConc, CBlock, PCo...
$ bsmt_cond       <fct> Typical, No_Basement, No_Basement, Typical, Typical, T...
$ bsmt_exposure   <fct> No, No_Basement, No_Basement, No, No, Av, Av, Av, No, ...
$ bsmt_fin_type_1 <fct> Unf, No_Basement, No_Basement, BLQ, LwQ, GLQ, GLQ, GLQ...
$ bsmt_fin_type_2 <fct> Unf, No_Basement, No_Basement, Rec, Unf, Unf, Unf, Unf...
$ heating         <fct> GasA, Wall, GasA, GasW, GasA, GasA, GasA, GasA, GasA, ...
$ heating_qc      <fct> Good, Fair, Typical, Fair, Fair, Excellent, Typical, E...
$ central_air     <fct> Y, N, Y, N, Y, Y, Y, Y, Y, Y, Y, Y, Y, Y, Y, Y, Y, Y, ...
$ electrical      <fct> SBrkr, FuseF, SBrkr, SBrkr, FuseA, SBrkr, SBrkr, SBrkr...
$ functional      <fct> Typ, Typ, Typ, Maj2, Typ, Typ, Typ, Typ, Typ, Typ, Typ...
```

```
$ garage_type      <fct> Attchd, Detchd, Attchd, Attchd, Detchd, Attchd, Attchd...
$ garage_finish    <fct> Fin, Unf, Fin, Unf, Unf, Fin, RFn, RFn, RFn, RFn, Unf,...
$ garage_cond      <fct> Typical, Typical, Good, Typical, Typical, Typical, Typ...
$ paved_drive      <fct> Paved, Paved, Paved, Paved, Paved, Paved, Paved, Paved...
$ pool_qc          <fct> No_Pool, No_Pool, No_Pool, No_Pool, No_Pool, No_Pool, ...
$ fence            <fct> Minimum_Privacy, No_Fence, No_Fence, No_Fence, No_Fenc...
$ misc_feature     <fct> None, None, None, None, None, None, None, None, None, ...
$ sale_condition   <fct> Normal, Normal, Normal, Normal, Normal, Normal, Normal...
```

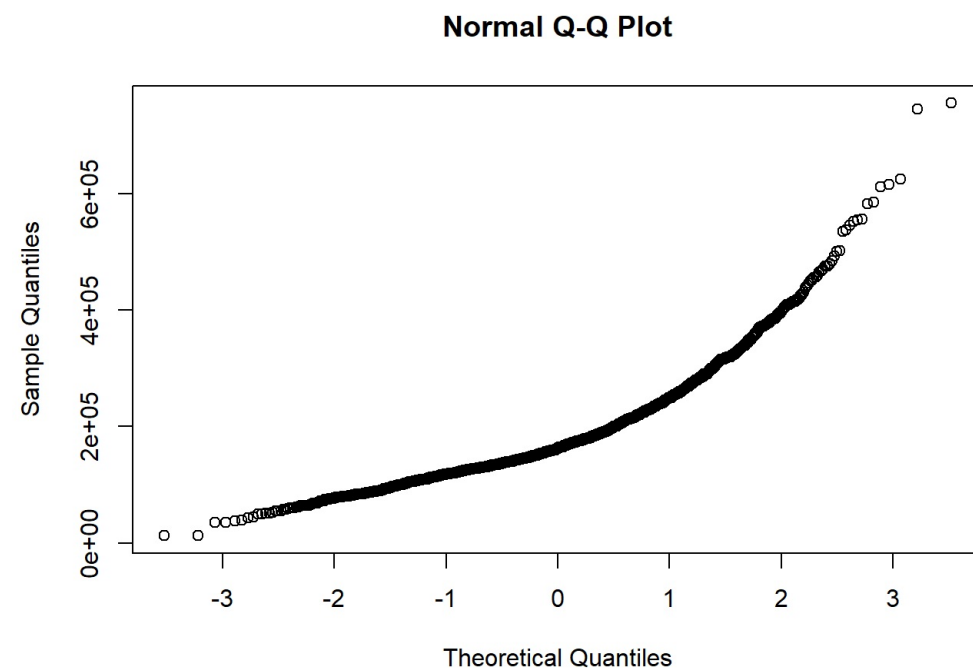
Initial EDA

The model we want to create is: `sale_price ~ < set of Xs >`. Let's first inspect the response variable.

```
# plot response variable
# -> seems skewed right and not normal
hist(data_train$sale_price)
```

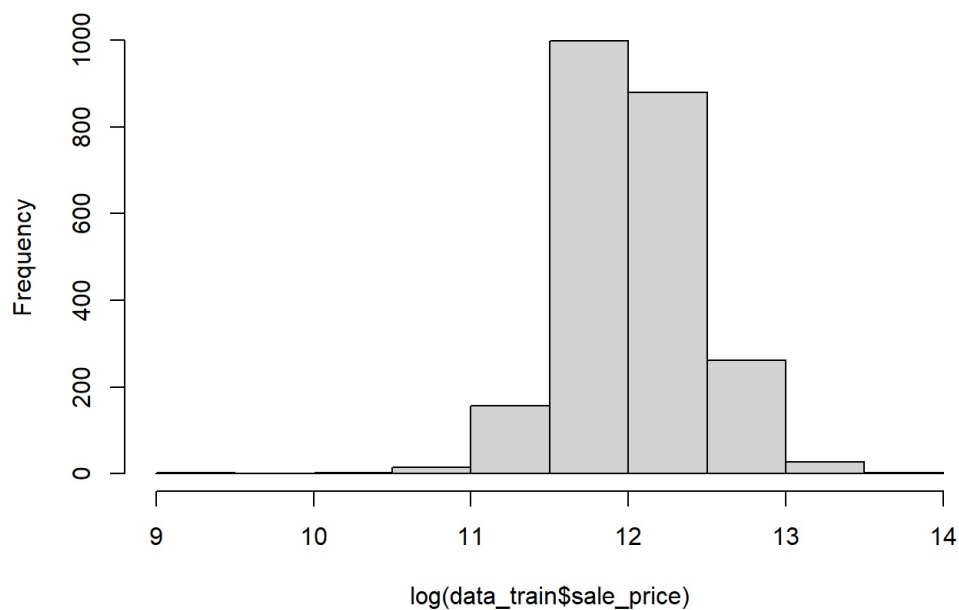


```
qqnorm(data_train$sale_price)
```



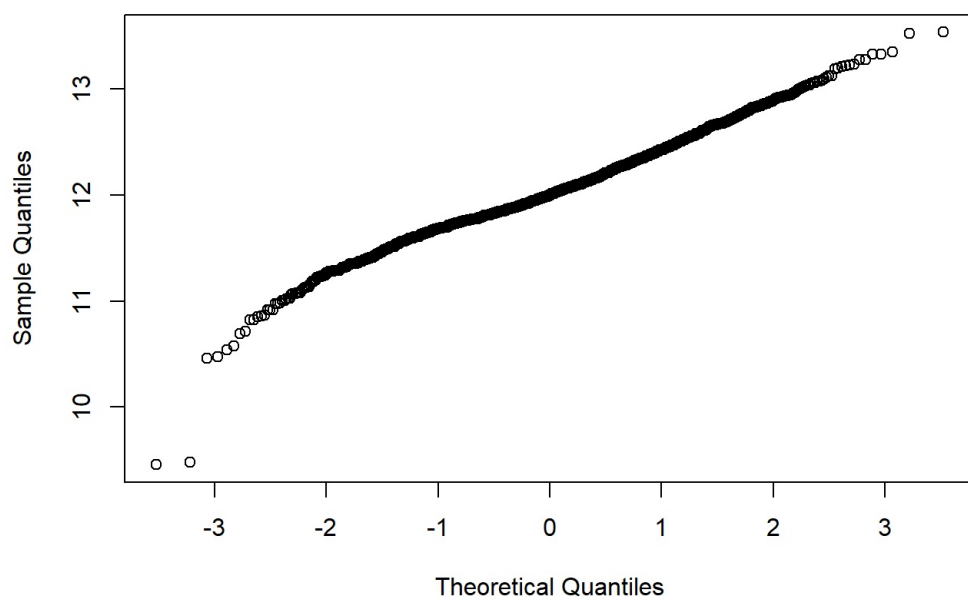
```
# -> try log transformation and recheck  
hist(log(data_train$sale_price))
```

Histogram of log(data_train\$sale_price)



```
qqnorm(log(data_train$sale_price))
```

Normal Q-Q Plot



The distribution of `sale_price` appears to be much more normal after transforming. So let's use `log(sale_price) ~ < set of Xs >` as our model.

This is technically a regression with a transformed response, so it is a generalized linear model (GLM). Once we make the transformation, everything works as usual, only the units and interpretations change.

Variable selection

Now try to find some $\backslash(X\backslash)$ variables to use in a model.

```
summary(data_train)
```

lot_frontage	lot_area	year_built	year_remod_add
Min. : 0.00	Min. : 1476	Min. :1872	Min. :1950
1st Qu.: 43.00	1st Qu.: 7420	1st Qu.:1954	1st Qu.:1966

Median	: 63.00	Median	: 9431	Median	:1974	Median	:1993
Mean	: 57.79	Mean	: 10229	Mean	:1972	Mean	:1985
3rd Qu.	: 78.00	3rd Qu.	: 11590	3rd Qu.	:2001	3rd Qu.	:2004
Max.	:313.00	Max.	:215245	Max.	:2010	Max.	:2010

mas_vnr_area	bsmt_fin_sf_1	bsmt_unf_sf	total_bsmt_sf
Min. : 0.0	Min. :0.000	Min. : 0.0	Min. : 0
1st Qu.: 0.0	1st Qu.:3.000	1st Qu.:216.0	1st Qu.: 796
Median : 0.0	Median :3.000	Median : 455.5	Median : 992
Mean : 100.8	Mean :4.124	Mean : 551.3	Mean :1055
3rd Qu.: 163.2	3rd Qu.:7.000	3rd Qu.: 785.0	3rd Qu.:1302
Max. :1600.0	Max. :7.000	Max. :2336.0	Max. :6110

first_flr_sf	second_flr_sf	gr_liv_area	bsmt_full_bath	full_bath
Min. : 334	Min. : 0.0	Min. : 334	Min. :0.000	Min. :0.000
1st Qu.: 876	1st Qu.: 0.0	1st Qu.:1126	1st Qu.:0.000	1st Qu.:1.000
Median :1090	Median : 0.0	Median :1448	Median :0.000	Median :2.000
Mean :1162	Mean : 337.3	Mean :1504	Mean :0.439	Mean :1.575
3rd Qu.:1390	3rd Qu.: 713.2	3rd Qu.:1749	3rd Qu.:1.000	3rd Qu.:2.000
Max. :5095	Max. :2065.0	Max. :5642	Max. :3.000	Max. :4.000

half_bath	bedroom_abv_gr	kitchen_abv_gr	tot_rms_abv_grd
Min. :0.0000	Min. :0.000	Min. :0.000	Min. : 2.000
1st Qu.:0.0000	1st Qu.:2.000	1st Qu.:1.000	1st Qu.: 5.000
Median :0.0000	Median :3.000	Median :1.000	Median : 6.000
Mean :0.3891	Mean :2.844	Mean :1.045	Mean : 6.433
3rd Qu.:1.0000	3rd Qu.:3.000	3rd Qu.:1.000	3rd Qu.: 7.000
Max. :2.0000	Max. :6.000	Max. :3.000	Max. :15.000

fireplaces	garage_cars	garage_area	wood_deck_sf
Min. :0.0000	Min. :0.000	Min. : 0.0	Min. : 0.00
1st Qu.:0.0000	1st Qu.:1.000	1st Qu.: 323.8	1st Qu.: 0.00
Median :1.0000	Median :2.000	Median : 480.0	Median : 0.00
Mean :0.6139	Mean :1.775	Mean : 475.0	Mean : 97.34
3rd Qu.:1.0000	3rd Qu.:2.000	3rd Qu.: 576.0	3rd Qu.: 172.00
Max. :4.0000	Max. :4.000	Max. :1488.0	Max. :1424.00

open_porch_sf	enclosed_porch	screen_porch	sale_price
Min. : 0.00	Min. : 0.00	Min. : 0.00	Min. : 12789
1st Qu.: 0.00	1st Qu.: 0.00	1st Qu.: 0.00	1st Qu.:130000
Median : 28.00	Median : 0.00	Median : 0.00	Median :162500
Mean : 47.29	Mean : 22.84	Mean : 16.25	Mean :182270
3rd Qu.: 70.00	3rd Qu.: 0.00	3rd Qu.: 0.00	3rd Qu.:215000
Max. :742.00	Max. :1012.00	Max. :576.00	Max. :755000

longitude	latitude	ms_zoning
Min. : -93.69	Min. : 41.99	Floating_Village_Residential: 122
1st Qu.: -93.66	1st Qu.: 42.02	Residential_High_Density : 23
Median : -93.64	Median : 42.03	Residential_Low_Density :1826
Mean : -93.64	Mean : 42.03	Residential_Medium_Density : 351
3rd Qu.: -93.62	3rd Qu.: 42.05	A_agr : 2
Max. : -93.58	Max. : 42.06	C_all : 19
		I_all : 1

street	alley	lot_shape	land_contour
Grvl: 10	Gravel : 87	Regular :1467	Bnk: 99
Pave:2334	No_Alley_Access:2189	Slightly_Irregular : 804	HLS: 97
	Paved : 68	Moderately_Irregular: 60	Low: 51
		Irregular : 13	Lvl:2097

lot_config	land_slope	condition_1	condition_2	bldg_type
Corner : 403	Gtl:2226	Norm :2035	Norm :2320	OneFam :1936
CulDSac: 141	Mod: 103	Feedr : 121	Feedr : 10	TwoFmCon: 47
FR2 : 73	Sev: 15	Artery : 71	Artery : 4	Duplex : 88
FR3 : 11		RRAn : 41	PosN : 4	Twnhs : 85
Inside :1716		PosN : 29	PosA : 2	TwnhsE : 188
		RRAe : 20	RRNn : 2	
		(Other): 27	(Other): 2	
house_style	overall_cond	roof_style	roof_matl	
One_Story :1193	Average :1332	Flat : 16	CompShg:2311	
Two_Story : 705	Above_Average: 434	Gable :1855	Tar&Grv: 18	
One_and_Half_Fin: 239	Good : 306	Gambrel: 19	WdShake: 6	
SLvl : 102	Very_Good : 110	Hip : 440	WdShngl: 6	
SFoyer : 66	Below_Average: 82	Mansard: 9	ClyTile: 1	

```

Two_and_Half_Unf: 18 Fair : 37 Shed : 5 Membran: 1
(Other) : 21 (Other) : 43 (Other): 1
mas_vnr_type exter_cond foundation bsmt_cond
BrkCmn : 17 Excellent: 9 BrkTil: 244 Excellent : 2
BrkFace: 707 Fair : 49 CBlock: 982 Fair : 76
CBlock : 1 Good : 238 PConc :1068 Good : 94
None :1416 Poor : 3 Slab : 36 No_Basement: 63
Stone : 203 Typical :2045 Stone : 10 Poor : 2
Wood : 4 Typical :2107

bsmt_exposure bsmt_fin_type_1 bsmt_fin_type_2 heating
Av : 338 ALQ :349 ALQ : 48 Floor: 1
Gd : 239 BLQ :215 BLQ : 56 GasA :2308
Mn : 191 GLQ :706 GLQ : 31 GasW : 19
No :1510 LwQ :132 LwQ : 75 Grav : 9
No_Basement: 66 No_Basement: 63 No_Basement: 64 OthW : 2
Rec :222 Rec : 85 Wall : 5
Unf :657 Unf :1985
heating_qc central_air electrical functional
Excellent:1223 N: 147 FuseA : 143 Typ :2188
Fair : 78 Y:2197 FuseF : 34 Min2 : 52
Good : 371 FuseP : 8 Min1 : 51
Poor : 3 Mix : 0 Mod : 29
Typical : 669 SBrkr :2158 Maj1 : 16
Unknown: 1 Maj2 : 6
(Other): 2
garage_type garage_finish garage_cond
Attchd :1398 Fin :584 Excellent: 3
Basement : 28 No_Garage:123 Fair : 59
BuiltIn : 148 RFn :671 Good : 10
CarPort : 14 Unf :966 No_Garage: 123
Detchd : 614 Poor : 9
More_Than_Two_Types: 20 Typical :2140
No_Garage : 122

paved_drive pool_qc fence misc_feature
Dirt_Gravel : 160 Excellent: 3 Good_Privacy : 101 Elev: 1
Partial_Pavement: 45 Fair : 2 Good_Wood : 80 Gar2: 3
Paved :2139 Good : 4 Minimum_Privacy : 248 None:2259
No_Pool :2332 Minimum_Wood_Wire: 10 Othr: 3
Typical : 3 No_Fence :1905 Shed: 77
TenC: 1

sale_condition
Abnorml: 149
AdjLand: 7
Alloca : 21
Family : 33
Normal :1930
Partial: 204

```

```

mod_data_train = lm(log(sale_price) ~ foundation+sale_condition, data=data_train)
summary(mod_data_train)

```

```

Call:
lm(formula = log(sale_price) ~ foundation + sale_condition, data = data_train)

```

```

Residuals:
    Min       1Q   Median       3Q      Max
-2.07275 -0.17803 -0.01073  0.18459  1.46126

```

```

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  11.52909    0.03285  350.957 < 2e-16 ***
foundationCBlock    0.17966    0.02337   7.687 2.20e-14 ***
foundationPConc    0.53079    0.02363  22.458 < 2e-16 ***
foundationSlab   -0.19778    0.05880  -3.363 0.000782 ***
foundationStone    0.12406    0.10538   1.177 0.239233
foundationWood     0.42690    0.16465   2.593 0.009580 **
sale_conditionAdjLand -0.19456    0.12633  -1.540 0.123680
sale_conditionAlloca  0.22281    0.07677   2.902 0.003739 **
sale_conditionFamily  0.05781    0.06290   0.919 0.358183
sale_conditionNormal  0.17920    0.02788   6.427 1.57e-10 ***

```

```
sale_conditionPartial 0.40264 0.03665 10.987 < 2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3266 on 2333 degrees of freedom
Multiple R-squared: 0.3612, Adjusted R-squared: 0.3585
F-statistic: 131.9 on 10 and 2333 DF, p-value: < 2.2e-16
```

```
mod_data_train1 = lm(log(sale_price) ~ condition_1+condition_2+functional, data=data_train)
summary(mod_data_train1)
```

Call:

```
lm(formula = log(sale_price) ~ condition_1 + condition_2 + functional,
    data = data_train)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.60537	-0.24868	-0.01815	0.23305	1.47277

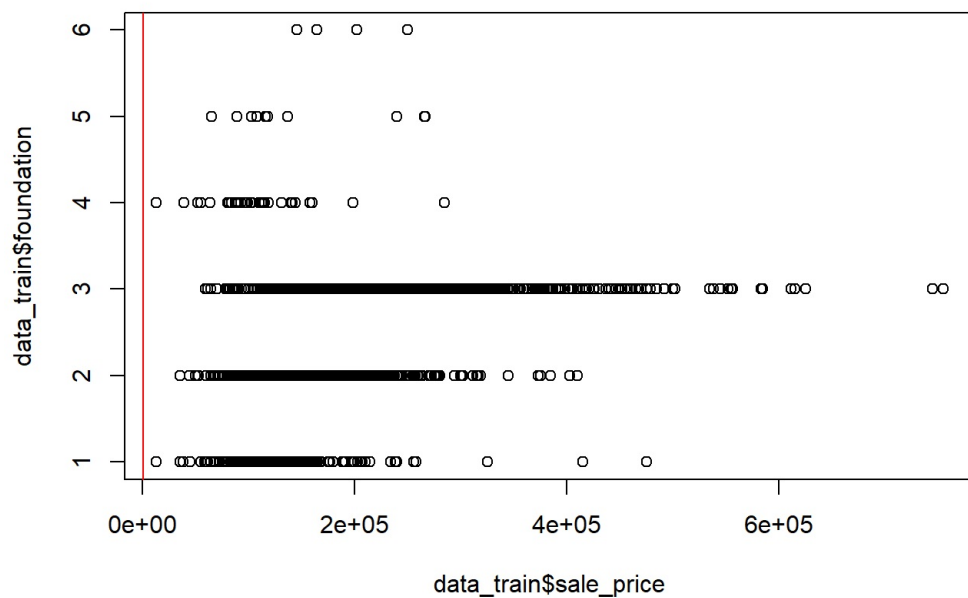
Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	11.362018	0.222698	51.020	< 2e-16 ***
condition_1Feedr	0.109348	0.059431	1.840	0.06591 .
condition_1Norm	0.317814	0.047977	6.624	4.32e-11 ***
condition_1PosA	0.532824	0.116012	4.593	4.61e-06 ***
condition_1PosN	0.493073	0.091462	5.391	7.71e-08 ***
condition_1RR Ae	0.080438	0.099635	0.807	0.41956
condition_1RR An	0.378638	0.079548	4.760	2.06e-06 ***
condition_1RR Ne	0.207146	0.201393	1.029	0.30379
condition_1RR Nn	0.450728	0.140453	3.209	0.00135 **
condition_2Feedr	-0.068045	0.236776	-0.287	0.77385
condition_2Norm	0.185620	0.200316	0.927	0.35421
condition_2PosA	1.035131	0.345007	3.000	0.00273 **
condition_2PosN	0.639372	0.290835	2.198	0.02802 *
condition_2RR Ae	0.487157	0.440494	1.106	0.26887
condition_2RR An	0.159421	0.440494	0.362	0.71745
condition_2RR Nn	-0.232293	0.342611	-0.678	0.49783
functionalMaj2	-0.453092	0.187505	-2.416	0.01575 *
functionalMin1	0.029872	0.112282	0.266	0.79023
functionalMin2	-0.002344	0.112133	-0.021	0.98332
functionalMod	0.016439	0.122117	0.135	0.89293
functionalSal	-1.556472	0.294425	-5.286	1.36e-07 ***
functionalTyp	0.196256	0.098330	1.996	0.04606 *

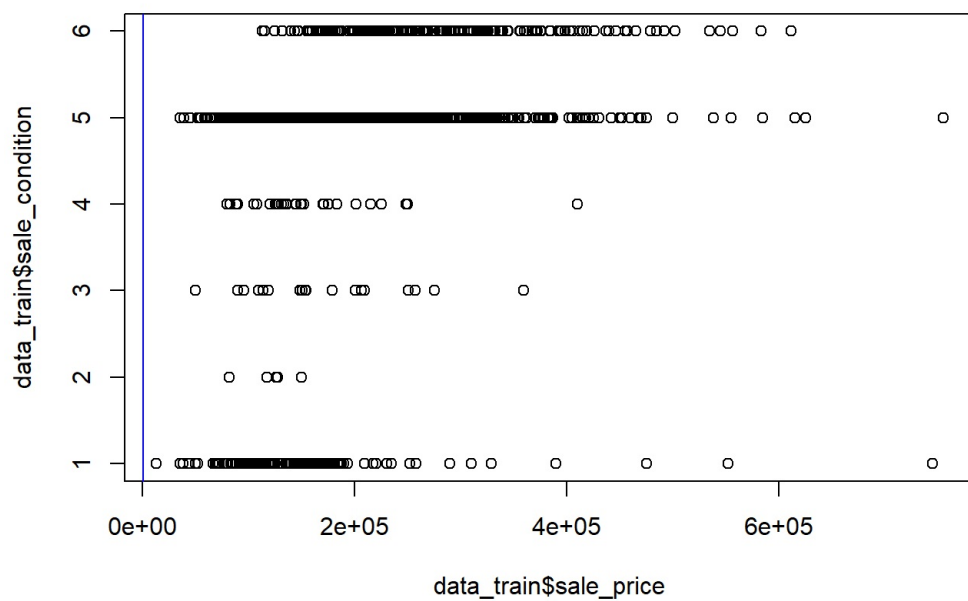
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3915 on 2322 degrees of freedom
Multiple R-squared: 0.08617, Adjusted R-squared: 0.07791
F-statistic: 10.43 on 21 and 2322 DF, p-value: < 2.2e-16

```
plot(x=data_train$sale_price, y=data_train$foundation)
abline(mod_data_train, col="red")
```



```
plot(x=data_train$sale_price, y=data_train$sale_condition)
abline(mod_data_train, col="blue")
```



```
coef(mod_data_train)
```

(Intercept)	foundationCBlock	foundationPConc
11.52908998	0.17965980	0.53078682
foundationSlab	foundationStone	foundationWood
-0.19777956	0.12405636	0.42690341
sale_conditionAdjLand	sale_conditionAlloca	sale_conditionFamily
-0.19456005	0.22281232	0.05781038
sale_conditionNormal	sale_conditionPartial	
0.17920468	0.40264278	

```
coef(mod_data_train1)
```

(Intercept)	condition_1Feedr	condition_1Norm	condition_1PosA
11.36201795	0.10934840	0.31781403	0.53282389
condition_1PosN	condition_1RR Ae	condition_1RRAn	condition_1RRNe

0.49307337	0.08043815	0.37863812	0.20714648
condition_1RRNn	condition_2Feedr	condition_2Norm	condition_2PosA
0.45072798	-0.06804493	0.18561953	1.03513105
condition_2PosN	condition_2RR Ae	condition_2RRAn	condition_2RRNn
0.63937237	0.48715736	0.15942055	-0.23229297
functionalMaj2	functionalMin1	functionalMin2	functionalMod
-0.45309152	0.02987241	-0.00234413	0.01643905
functionalSal	functionalTyp		
-1.55647159	0.19625564		

Prediction

Once you have some candidate models, see which one is the best by calculating the $\sqrt{\text{RMSE}}$.

```
area <- lm(log(sale_price)~foundation, data=data_train)
log_area <- lm(log(sale_price)~sale_condition, data=data_train)

yardstick::rmse_vec(truth=log(data_test$sale_price), estimate= predict(log_area, newdata=data_test))
```

```
[1] 0.3692361
```

```
yardstick::rmse_vec(truth=log(data_test$sale_price), estimate= predict(area, newdata=data_test))
```

```
[1] 0.3374639
```