

VIA 502E Data Mining Homework

Q1- Take the ames data from tidymodels package





#Q1

```
data(ames)

ames_split <- initial_split(ames, prop = 0.8, strata = Sale_Price)

ames_train <- training(ames_split)
ames_test <- testing(ames_split)
```

- Using prop and strata commands, ames_train and ames_test are splitted according to distribution of data points in Sale_Price.

Data		
ames	2930 obs. of 74 variables	
ames_split	Large mc_split (4 elements, 1 MB)	
ames_test	584 obs. of 74 variables	
ames_train	2346 obs. of 74 variables	

Q2- Set `Sale_Price` column as output and following features as input variables:

- MS_SubClass MS_Zoning Lot_Frontage Lot_Area Street Alley Lot_Shape Land_Contour Utilities Lot_Config

Q3- Fit a linear model using all the input variables listed above

```
# Q2 and Q3

linear_model <- lm(Sale_Price ~ MS_SubClass + MS_Zoning + Lot_Frontage + Lot_Area + Street+ Alley + Lot_Shape +
  Land_Contour + Utilities + Lot_Config,data = ames_train)
summary(linear_model)
```

- lm command is used for constructing a linear model in R. summary() fucntion made it possible to observe the model statistics.

Residuals:

Min	1Q	Median	3Q	Max
-263376	-37298	-10035	24152	469195

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	7.216e+04	2.512e+04	2.872	0.00411	**
MS_SubClassOne_story_1945_and_older	-5.504e+04	6.633e+03	-8.298	< 2e-16	***
MS_SubClassOne_story_with_Finished_Attic_All_Ages	-1.902e+02	2.819e+04	-0.007	0.99462	
MS_SubClassOne_and_Half_story_Unfinished_All_Ages	-4.392e+04	1.595e+04	-2.754	0.00594	**
MS_SubClassOne_and_Half_story_Finished_All_Ages	-2.645e+04	5.023e+03	-5.267	1.52e-07	***
MS_SubClassTwo_story_1946_and_Newer	5.098e+04	3.675e+03	13.871	< 2e-16	***
MS_SubClassTwo_story_1945_and_older	-2.862e+03	7.266e+03	-0.394	0.69363	
MS_SubClassTwo_and_Half_story_All_Ages	3.415e+04	1.520e+04	2.246	0.02477	*
MS_SubClassSplit_or_Multilevel	-1.340e+04	6.996e+03	-1.916	0.05551	.
MS_SubClassSplit_Foyer	-2.763e+04	1.035e+04	-2.671	0.00762	**
MS_SubClassDuplex_All_styles_and_Ages	-3.302e+04	7.114e+03	-4.642	3.64e-06	***
MS_SubClassOne_story_PUD_1946_and_Newer	4.486e+04	5.908e+03	7.593	4.51e-14	***
MS_SubClassOne_and_Half_story_PUD_All_Ages	-2.612e+04	6.265e+04	-0.417	0.67674	
MS_SubClassTwo_story_PUD_1946_and_Newer	-3.806e+03	7.524e+03	-0.506	0.61301	
MS_SubClassPUD_Multilevel_Split_Level_Foyer	-1.419e+04	1.803e+04	-0.787	0.43142	
MS_SubClassTwo_Family_conversion_All_styles_and_Ages	-4.439e+04	9.688e+03	-4.582	4.85e-06	***
MS_ZoningResidential_High_Density	-4.741e+04	1.628e+04	-2.913	0.00362	**
MS_ZoningResidential_Low_Density	-3.237e+04	7.314e+03	-4.426	1.00e-05	***
MS_ZoningResidential_Medium_Density	-4.643e+04	8.062e+03	-5.759	9.56e-09	***
MS_ZoningA_agr	-2.038e+05	4.485e+04	-4.543	5.83e-06	***
MS_ZoningC_all	-7.999e+04	1.720e+04	-4.650	3.50e-06	***
MS_ZoningI_all	-1.260e+04	9.204e+04	-0.137	0.89109	
Lot_Frontage	5.071e+02	4.297e+01	11.803	< 2e-16	***
Lot_Area	2.056e+00	2.058e-01	9.991	< 2e-16	***
StreetPave	5.965e+04	2.178e+04	2.739	0.00621	**
AlleyNo_Alley_Access	7.615e+03	7.068e+03	1.077	0.28144	
AlleyPaved	1.093e+04	1.137e+04	0.961	0.33662	
Lot_ShapeSlightly_Irregular	2.083e+04	3.205e+03	6.500	9.81e-11	***
Lot_ShapeModerately_Irregular	1.788e+04	8.865e+03	2.017	0.04384	*
Lot_ShapeIrregular	-2.473e+04	1.903e+04	-1.300	0.19388	
Land_ContourHLS	6.192e+04	9.164e+03	6.757	1.78e-11	***
Land_ContourLow	1.104e+04	1.144e+04	0.965	0.33479	
Land_ContourLv1	9.927e+03	6.844e+03	1.450	0.14706	
UtilitiesNoSewa	-5.571e+04	6.241e+04	-0.893	0.37219	
UtilitiesNoSewr	-6.654e+04	6.319e+04	-1.053	0.29249	
Lot_ConfigCulDSac	2.584e+04	6.494e+03	3.980	7.12e-05	***
Lot_ConfigFR2	-1.053e+04	8.264e+03	-1.274	0.20265	
Lot_ConfigFR3	1.367e+04	1.758e+04	0.778	0.43683	
Lot_ConfigInside	2.051e+03	3.464e+03	0.592	0.55376	

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

Residual standard error: 62140 on 2307 degrees of freedom
Multiple R-squared: 0.4038, Adjusted R-squared: 0.394
F-statistic: 41.12 on 38 and 2307 DF, p-value: < 2.2e-16

Q4 – Use tidymodel for necessary preprocessing steps as you see fit. (normalization, transformation, etc.)

```
# Q4
simple_ames <-
  recipe(sale_price ~ MS_SubClass + MS_Zoning + Lot_Frontage + Lot_Area + StreetPave + Alley + Lot_Shape + Land_Contour + Utilities + Lot_Config,
    data = ames_train) %>%
  step_dummy(all_nominal()) %>%
  prep(training = ames_train)

train_new <- bake(simple_ames, new_data = NULL)
test_new <- bake(simple_ames, new_data = ames_test)
```

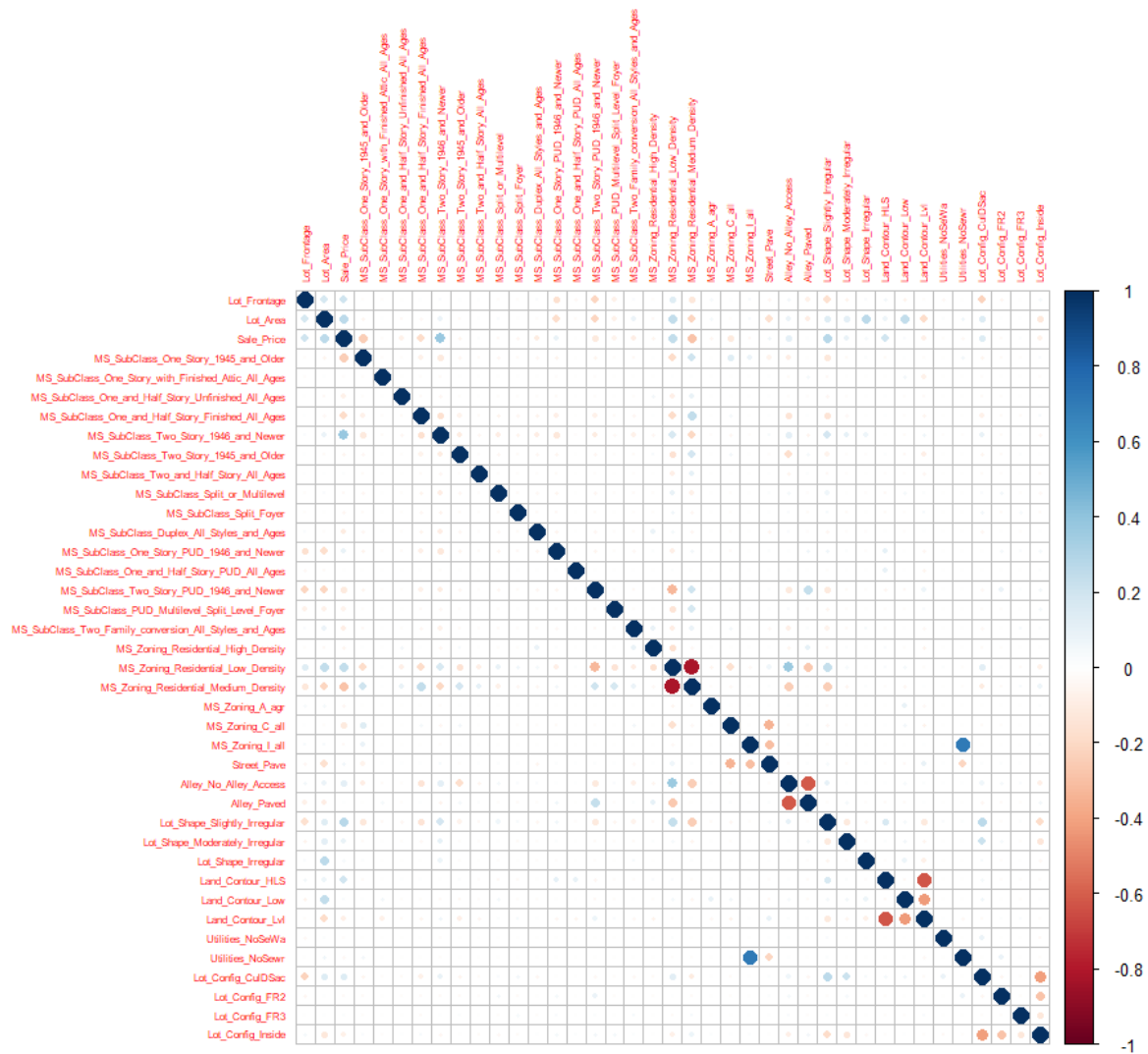
- Like cooking a dinner; Recipe, Prep and Bake is used for preprocessing. Since variables are categorical i used step_dummy function and transformed categorical variables to nominal.

**Q5- Look at the correlation values, can you see multicollinearity if yes, remove necessary variables.
(You can use `corrplot()` function from corrplot package)**

```
# Q5 Getting correlations between variables

correlations <- cor(train_new, method="pearson")
correlations
corrplot(correlations, method = "circle", tl.cex = 0.5)
```

- Used pearson method to observe correlations between variables in preprocessed train_new data.



As we can see from the plot, there are some highly correlated variables:

<i>MS_Zoning_Residential_Medium_Density</i>	<i>MS_Zoning_Residential_Low_Density</i>
<i>Alley_No_Alley_Access</i>	<i>Alley_No_Paved</i>
<i>Land_Contour_Lvl</i>	<i>Land_Contour_HLS</i>

- *Removed one variable from each pair to prevent multicollinearity.*

```
train_new <- select(train_new, ~'Alley_No_Alley_Access', ~'MS_Zoning_Residential_Medium_Density', ~'Land_Contour_HLS')
test_new <- select(test_new, ~'Alley_No_Alley_Access', ~'MS_Zoning_Residential_Medium_Density', ~'Land_Contour_HLS')
```

Q6- Look at the p -values in linear regression if you see statistically insignificant values, remove them.

Q6

```
pvalues <- lm(Sale_Price ~ MS_SubClass + MS_Zoning + Lot_Frontage + Lot_Area + Street + Alley
+ Lot_Shape + Land_Contour + Utilities + Lot_Config, data = ames)
summary(pvalues)
```

- *If the p value of a variable is greater than 0.05, we can say that it is insignificant. R really helps us to find the significant values, indicating them with stars. So i eliminated the insignifiant ones and tested the model like that.*

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	8.278e+04	2.304e+04	3.594	0.000332	***
MS_SubClassOne_Story_1945_and_Older	-5.539e+04	6.126e+03	-9.042	< 2e-16	***
MS_SubClassOne_Story_with_Finished_Attic_All_Ages	-8.331e+03	2.593e+04	-0.321	0.747975	
MS_SubClassOne_and_Half_Story_Unfinished_All_Ages	-4.007e+04	1.518e+04	-2.639	0.008357	**
MS_SubClassOne_and_Half_Story_Finished_All_Ages	-2.581e+04	4.583e+03	-5.633	1.95e-08	***
MS_SubClassTwo_Story_1946_and_Newer	4.698e+04	3.308e+03	14.202	< 2e-16	***
MS_SubClassTwo_Story_1945_and_Older	-4.809e+03	6.416e+03	-0.750	0.453576	
MS_SubClassTwo_and_Half_Story_All_Ages	3.409e+04	1.354e+04	2.518	0.011855	*
MS_SubClassSplit_or_Multilevel	-1.496e+04	6.120e+03	-2.445	0.014549	*
MS_SubClassSplit_Foyer	-2.670e+04	9.313e+03	-2.867	0.004177	**
MS_SubClassDuplex_All_Styles_and_Ages	-3.109e+04	6.379e+03	-4.874	1.15e-06	***
MS_SubClassOne_Story_PUD_1946_and_Newer	4.189e+04	5.265e+03	7.956	2.53e-15	***
MS_SubClassOne_and_Half_Story_PUD_All_Ages	-2.514e+04	6.320e+04	-0.398	0.690812	
MS_SubClassTwo_Story_PUD_1946_and_Newer	-6.087e+03	6.878e+03	-0.885	0.376291	
MS_SubClassPUD_Multilevel_Split_Level_Foyer	-1.492e+04	1.596e+04	-0.935	0.349964	
MS_SubClassTwo_Family_conversion_All_Styles_and_Ages	-4.161e+04	8.581e+03	-4.849	1.31e-06	***
MS_ZoningResidential_High_Density	-5.368e+04	1.367e+04	-3.927	8.82e-05	***
MS_ZoningResidential_Low_Density	-3.484e+04	6.538e+03	-5.328	1.07e-07	***
MS_ZoningResidential_Medium_Density	-5.029e+04	7.290e+03	-6.898	6.45e-12	***
MS_ZoningA_agr	-2.015e+05	4.511e+04	-4.466	8.26e-06	***
MS_ZoningC_all	-8.273e+04	1.482e+04	-5.581	2.61e-08	***
MS_ZoningI_all	-1.260e+05	5.281e+04	-2.386	0.017115	*
Lot_Frontage	5.013e+02	3.915e+01	12.804	< 2e-16	***
Lot_Area	1.986e+00	1.769e-01	11.225	< 2e-16	***
StreetPave	4.634e+04	1.991e+04	2.327	0.020014	*
AlleyNo_Alley_Access	9.525e+03	6.454e+03	1.476	0.140065	
AlleyPaved	9.107e+03	1.051e+04	0.866	0.386365	
Lot_ShapeSlightly_Irregular	2.311e+04	2.877e+03	8.031	1.39e-15	***
Lot_ShapeModerately_Irregular	2.081e+04	7.905e+03	2.632	0.008523	**
Lot_ShapeIrregular	-2.009e+04	1.634e+04	-1.229	0.218990	
Land_ContourHLS	6.237e+04	8.427e+03	7.402	1.75e-13	***
Land_ContourLow	5.285e+03	1.058e+04	0.500	0.617454	
Land_ContourLvl	1.319e+04	6.190e+03	2.131	0.033174	*
UtilitiesNoSewa	-5.514e+04	6.300e+04	-0.875	0.381497	
UtilitiesNoSewr	-1.801e+04	5.216e+04	-0.345	0.729849	
Lot_ConfigCuI_DSac	2.398e+04	5.876e+03	4.081	4.61e-05	***
Lot_ConfigFR2	-6.268e+03	7.525e+03	-0.833	0.404946	
Lot_ConfigFR3	1.182e+04	1.709e+04	0.692	0.489267	
Lot_ConfigInside	3.979e+03	3.157e+03	1.260	0.207677	

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

```
train_excluded <- select(train_new, ~MS_SubClass_One_Story_with_Finished_Attic_All_Ages', ~MS_SubClass_Two_Story_1945_and_Older',
~'MS_SubClass_One_and_Half_Story_PUD_All_Ages', ~'MS_SubClass_Two_Story_PUD_1946_and_Newer',
~'MS_SubClass_PUD_Multilevel_Split_Level_Foyer', ~'Alley_Paved', ~'Lot_Shape_Irregular', ~'Land_Contour_Low',
~'Utilities_NoSewa', ~'Utilities_NoSewr', ~'Lot_Config_FR2', ~'Lot_Config_FR3', ~'Lot_Config_Inside' )

test_excluded <- select(test_new, ~'MS_SubClass_One_Story_with_Finished_Attic_All_Ages', ~'MS_SubClass_Two_Story_1945_and_Older',
~'MS_SubClass_One_and_Half_Story_PUD_All_Ages', ~'MS_SubClass_Two_Story_PUD_1946_and_Newer',
~'MS_SubClass_PUD_Multilevel_Split_Level_Foyer', ~'Alley_Paved', ~'Lot_Shape_Irregular', ~'Land_Contour_Low',
~'Utilities_NoSewa', ~'Utilities_NoSewr', ~'Lot_Config_FR2', ~'Lot_Config_FR3', ~'Lot_Config_Inside' )
```

Q7- Report your final model and its performance on the testing data

```
mdl <- lm(Sale_Price ~ . , data = train_excluded)
```

```
summary(mdl)
glance(mdl)
tidy(mdl)
```

```
predict(mdl, test_excluded)
```

- Used glance and tidy functions to observe model.
- Predicted Sale_Price for the test data is given with the last command.

```
> glance(mdl)
# A tibble: 1 x 12
  r.squared adj.r.squared sigma statistic p.value df logLik AIC BIC deviance df.residual nobs
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <int> <int>
1 0.401 0.395 62108. 62.1 2.16e-236 25 -29208. 58469. 58625. 8.95e12 2320 2346

> tidy(mdl)
# A tibble: 26 x 5
  term estimate std.error statistic p.value
  <chr> <dbl> <dbl> <dbl> <dbl>
1 (Intercept) 81408. 23460. 3.47 5.30e- 4
2 Lot_Frontage 516. 41.4 12.4 1.81e-34
3 Lot_Area 2.01 0.191 10.5 2.25e-25
4 MS_SubClass_One_Story_1945_and_Older -53868. 6305. -8.54 2.31e-17
5 MS_SubClass_One_and_Half_Story_Unfinished_All_Ages -42791. 15785. -2.71 6.76e- 3
6 MS_SubClass_One_and_Half_Story_Finished_All_Ages -25534. 4661. -5.48 4.77e- 8
7 MS_SubClass_Two_Story_1946_and_Newer 51194. 3563. 14.4 6.46e-45
8 MS_SubClass_Two_and_Half_Story_All_Ages 34902. 14959. 2.33 1.97e- 2
9 MS_SubClass_Split_or_Multilevel -13030. 6926. -1.88 6.00e- 2
10 MS_Subclass_Split_Foyer -26676. 10291. -2.59 9.60e- 3
# ... with 16 more rows

> predict(mdl, test_excluded)
1 2 3 4 5 6 7 8 9 10 11 12
167566.90 256094.67 250395.96 216694.38 186095.86 195800.18 216469.78 141279.11 227702.31 239839.54 196443.80 207945.12
13 14 15 16 17 18 19 20 21 22 23 24
215486.64 228724.78 207968.59 207909.57 122009.11 265766.81 266027.16 165192.51 165192.51 231605.85 176497.06 146540.72
25 26 27 28 29 30 31 32 33 34 35 36
124150.91 157517.98 178882.16 181798.54 176605.96 196027.56 220222.30 80995.33 98236.48 92412.73 128507.35 147876.00
37 38 39 40 41 42 43 44 45 46 47 48
153557.75 154821.85 130887.67 171891.77 166651.45 166715.92 121451.45 167700.20 181210.64 193928.64 284402.21 146656.49
49 50 51 52 53 54 55 56 57 58 59 60
222337.85 167553.44 140438.49 156510.91 170438.22 143498.08 168611.64 214971.52 159811.50 129230.33 99851.66 124291.84
61 62 63 64 65 66 67 68 69 70 71 72
246587.88 93811.19 90419.85 226004.16 145336.03 125129.90 115981.84 136638.73 181798.54 143039.10 238812.20 173218.88
73 74 75 76 77 78 79 80 81 82 83 84
172398.95 204970.43 134102.19 156512.22 162381.12 166491.32 115558.73 180619.56 134530.03 134560.26 202807.66 251772.36
85 86 87 88 89 90 91 92 93 94 95 96
204625.48 200487.17 224569.40 247124.09 212716.93 222686.08 192232.90 192232.90 242388.59 175279.61 206546.14 216049.97
97 98 99 100 101 102 103 104 105 106 107 108
151974.11 243800.87 223412.06 227653.01 247570.30 226779.43 235109.19 204922.92 268331.00 273684.16 172282.40 223061.16
109 110 111 112 113 114 115 116 117 118 119 120
168262.02 178817.69 165396.01 162490.14 240705.40 163754.79 229206.22 163340.17 178011.77 152477.82 207618.42 246368.12
121 122 123 124 125 126 127 128 129 130 131 132
191527.65 179623.61 179579.50 178300.62 185425.29 175298.89 164666.90 231839.99 167700.20 155770.01 111651.21 168838.25
133 134 135 136 137 138 139 140 141 142 143 144
223053.85 124331.49 115661.60 113529.39 151623.53 154361.55 92920.22 117627.41 114437.86 114437.86 90655.68 152958.48
145 146 147 148 149 150 151 152 153 154 155 156
194803.62 90228.63 127743.69 144101.94 142528.92 179513.86 140827.34 191009.97 171766.40 171766.40 108152.78 186617.69
157 158 159 160 161 162 163 164 165 166 167 168
193838.91 145811.03 251124.89 125047.25 101029.78 194187.40 170241.19 208663.47 181100.89 164621.58 230818.06 243138.73
169 170 171 172 173 174 175 176 177 178 179 180
192069.53 177551.07 155762.93 143852.52 156510.91 242353.59 167004.46 156021.75 209991.11 162151.53 214971.52 177222.07
181 182 183 184 185 186 187 188 189 190 191 192
100608.09 162864.67 159164.96 156665.68 212160.21 116968.45 153268.26 210032.71 149059.73 182004.69 247195.07 115149.72
193 194 195 196 197 198 199 200 201 202 203 204
151885.46 234755.94 239707.41 321073.27 279750.63 196911.84 190361.46 190154.89 230818.06 230979.24 165136.74 115558.73
205 206 207 208 209 210 211 212 213 214 215 216
254738.17 199147.82 221552.28 269693.21 235384.45 258045.16 200972.07 140916.44 171590.25 228178.13 252007.58 184232.56
217 218 219 220 221 222 223 224 225 226 227 228
206828.83 214618.06 203737.68 205673.06 267569.41 267922.00 216374.96 232941.59 247980.63 205573.46 207909.57 161172.24
229 230 231 232 233 234 235 236 237 238 239 240
186031.47 169567.40 164418.83 194449.24 226176.80 188564.38 176198.45 183771.99 196166.47 161714.44 122208.43 114484.08
241 242 243 244 245 246 247 248 249 250 251 252
164981.91 175594.00 179526.48 177096.09 162279.00 171836.28 168751.93 200944.74 160884.34 139214.45 111672.89 124635.51
253 254 255 256 257 258 259 260 261 262 263 264
87297.14 154041.30 145460.35 87306.61 139971.81 166141.84 112614.55 22430.29 109778.78 216297.50 99206.41 162402.32
265 266 267 268 269 270 271 272 273 274 275 276
113383.34 171860.45 153312.71 194623.98 152291.11 144188.04 272769.82 169800.04 129651.58 131152.24 236810.83 190915.03
277 278 279 280 281 282 283 284 285 286 287 288
188071.38 184029.17 216555.68 262009.97 234918.19 253310.00 155762.93 191284.37 218567.19 263125.71 167961.07 218378.01
289 290 291 292 293 294 295 296 297 298 299 300
174972.70 156492.78 297008.72 137496.57 144755.50 109390.31 163547.58 133754.79 162420.58 181287.41 214500.90 141757.47
301 302 303 304 305 306 307 308 309 310 311 312
244851.82 109362.29 183825.64 89190881.46 170109.81 251968.21 161644.86 168768.86 123397.21 106716.16 116151.83 115386.48
313 314 315 316 317 318 319 320 321 322 323 324
```