Statistical packages - report 1

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1 Introduction

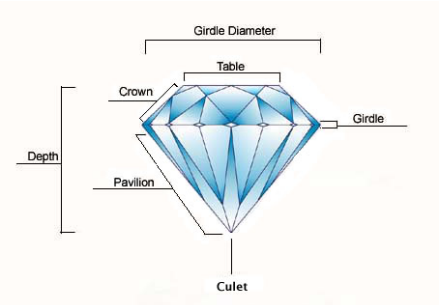


Figure 1: Anatomy of diamond. *source: https://www.everything-wedding-rings.com*

For this report we have decided to analyse "Diamonds", dataset about the features and prices of stones which we have found on Kaggle [https://www.kaggle.com/shivam2503/diamonds]. It contains 54940 records and each one has 11 columns with different variables. First one is irrelevant, because it's just index number. Then we have numerical variables - x, y, z that describe size of diamond in each of three dimensions.There is also weight given in carats. Today, a carat is equal to exactly 0.2 grams). Carat weight is unrelated to the similar sounding karat, which refers to gold's purity. Next we have two variables describing percentage relation between appropriate measures within the diamond. Depth is the height of a diamond, measured from the culet to the table, divided by its average girdle diameter. Table is the width of the diamond's table expressed

as a percentage of its average diameter. The last numerical variable is price. Coming to discrete variables we have cut describing the quality of diamond's cut: Fair, Good, Very Good, Premium, Ideal. The cut describes the symmetry proportioning and polish of the diamond. Then there is color of diamond ranged descending from D to J. The later letter in the alphabet the more yellow. And the last is clarity of particular diamond with possible values: FL,IF, VVS1, VVS2, VS1, VS2, SI1, SI2, I1, I2, I3 (ordering from best to worse). It refers to the absence of inclusions and blemishes.

2 Aim of analysis

Jewelry is a kind of art made of expensive raw material. These art is based on precision and integrity but because of the fact that it is an art sometimes the defects increase the price. These defects make diamond unique and uniqueness is the main part of art. In our analyze we would like to check which features influence the price and at which level. Besides we are interested how important are all features that are influenced by jeweler(shape, cut) and that what are natural (color, clarity). The figure 2 is a visualisation of distribution of prices. The chart shows that the most common are relativly cheap diamonds. Then if the price increase the diamond becomes rare.

3 Data preprocessing

This, first step of working with data we started from removing unnecessary variables. We remove the index column, because it is irrelevant information. Then we looked for missing data. Dataset didn't contain any NaNs, but some values were impossible to occur in reality. To handle such situations we changed every zero from x, y or z column to NA, because this will make our upcoming work easier. We also checked if other numerical columns contain zeros, but they didn't. Next,we focused on ensuring that categorical variables don't contain typos. In order to do that we just looked at all values they take, but there wasn't need any cleaning. We didn't deal with outliers, because we will do it within next steps of analysis.

```
> diamonds_data <- diamonds_data[2:11] #data cleaning - removing unnecessary variables
> #changing 0 to NAs
> diamonds_data$z[diamonds_data$z==0] = NA
> diamonds_data$x[diamonds_data$x==0] = NA
> diamonds_data$y[diamonds_data$y==0] = NA
> any(is.na(diamonds_data)) #check if there are any nulls in our dataset

[1] TRUE

> diamonds_data_omited <- na.omit(diamonds_data)
> #checking for typos
> summary(diamonds_data$cut)

     Fair      Good     Ideal   Premium Very Good
     1610      4906     21551     13791     12082

> summary(diamonds_data$color)

    D     E     F     G     H     I     J
 6775  9797  9542 11292  8304  5422  2808

> summary(diamonds_data$clarity)
```

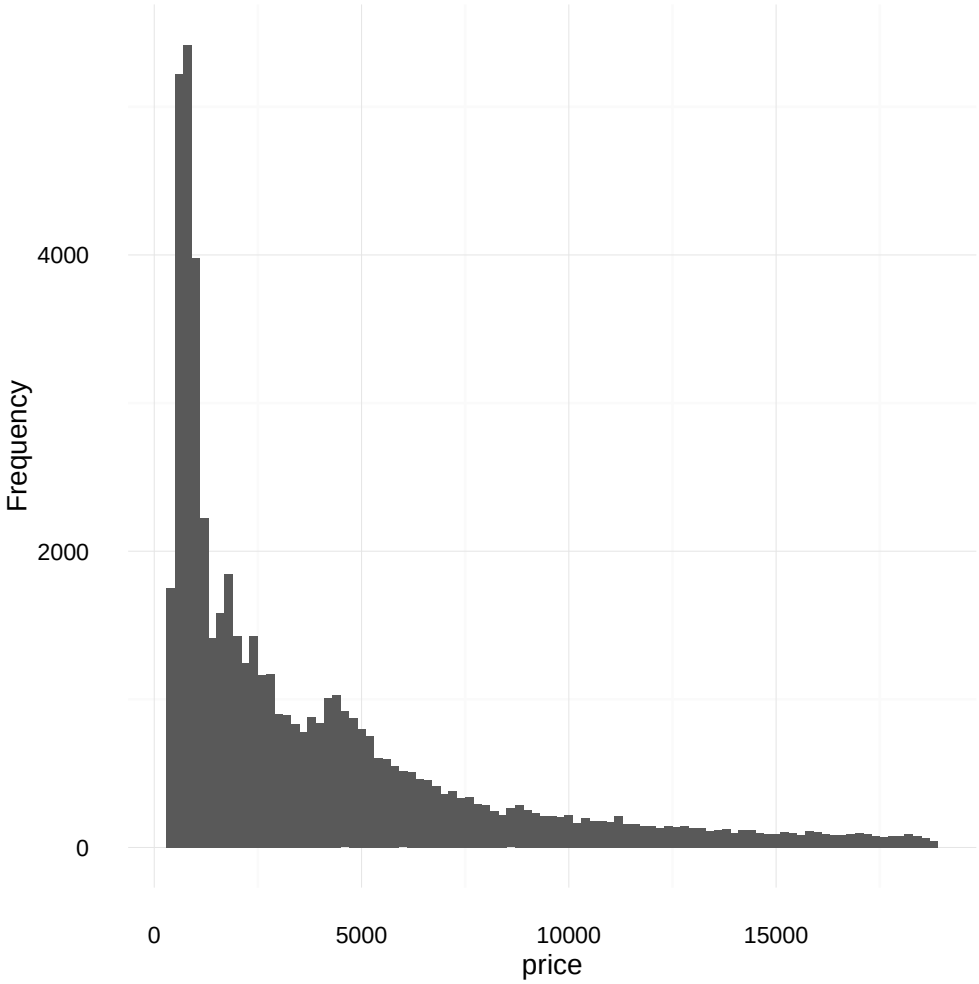


Figure 2: Distributionof values of price in our dataset

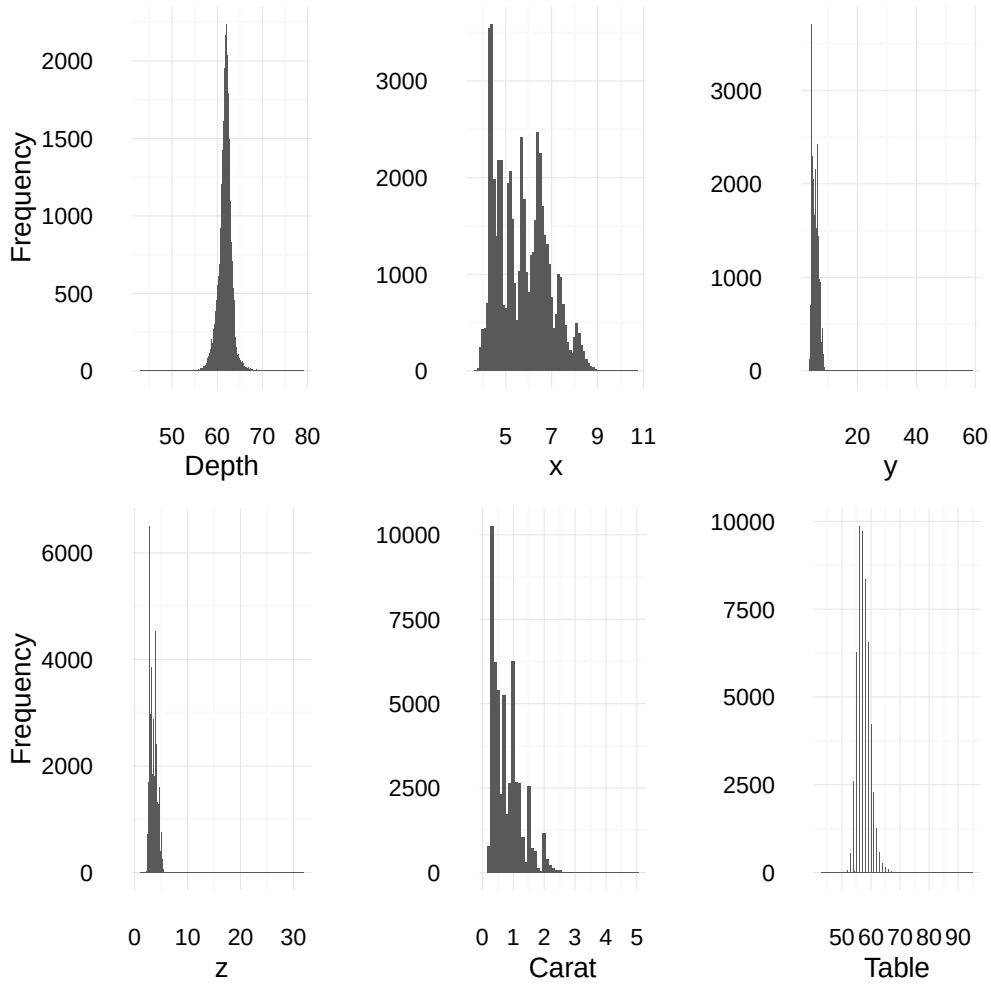


Figure 3: Distributions of each of continous variables

```
  I1    IF   SI1   SI2   VS1   VS2  VVS1  VVS2
 741  1790 13065  9194  8171 12258  3655  5066
```

Before we started fitting the model whe have made quick look on the data. In figures and we can see te histograms and boxplots. The plot of depth is symetric similar to the bell curve. The next one (x) is much more dispersed. The distributions of y, z and espessialy table shows that this data are have small differences in each group.

4 Model fitting

4.1 Continuous variables

To fit model to data we use function glmulti from package glmulti. To reduce complexity of model at this step we decided to choose maximum number of used variables to 3. We checked models with different distribution families. These were Gaussian, Poisson and Gamma. It turned out that Gamma model provides the best fit

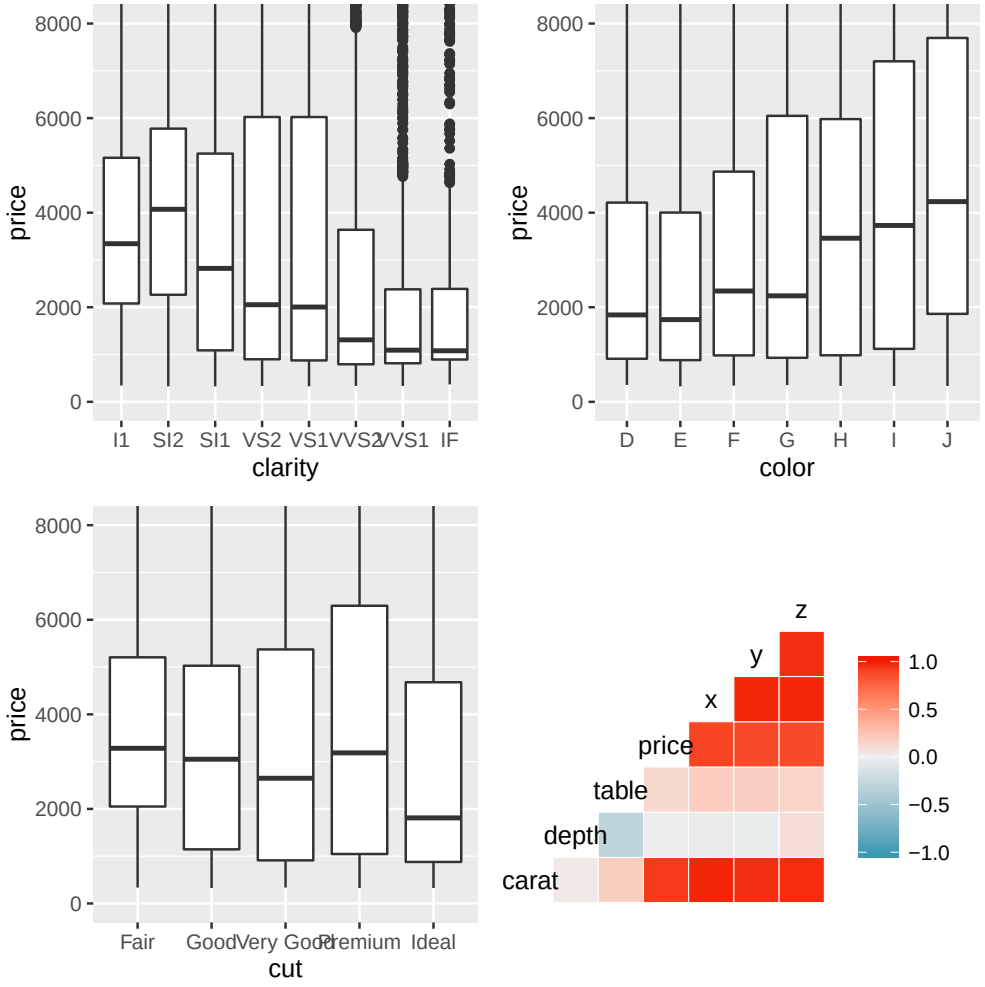
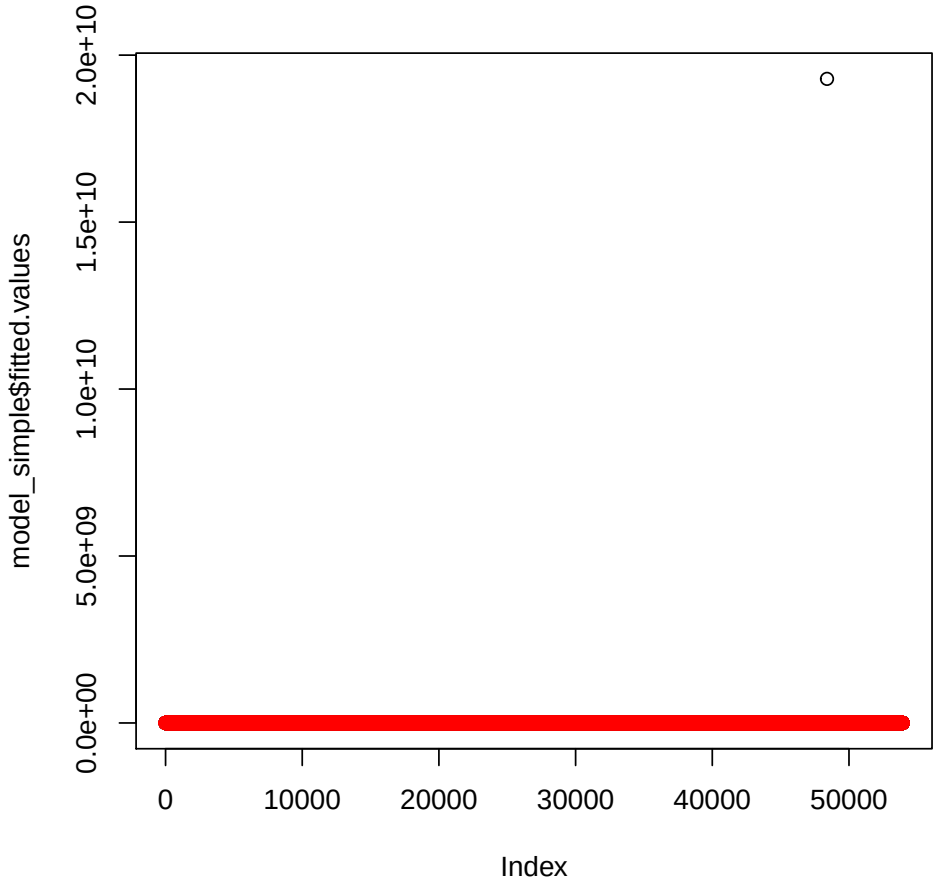


Figure 4: Boxplots of price depending on values of categorical variables and the corelation chart between each two variables

under the BIC criteria. The formula of this model is as follows:

$$\text{cost} = -1.0777\text{carat} + 0.5714z + 0.9717x + 1.0882. \tag{1}$$

```
> model_simple <- glm(formula = price~z+x+carat, data = diamonds_data_omited,
+                     family = Gamma(link = 'log'))
> plot(model_simple$fitted.values)
> points(diamonds_data_omited$price, col = 'red')
```



A the plot we can clearly see that there outliers, but we will handle it in next sections.

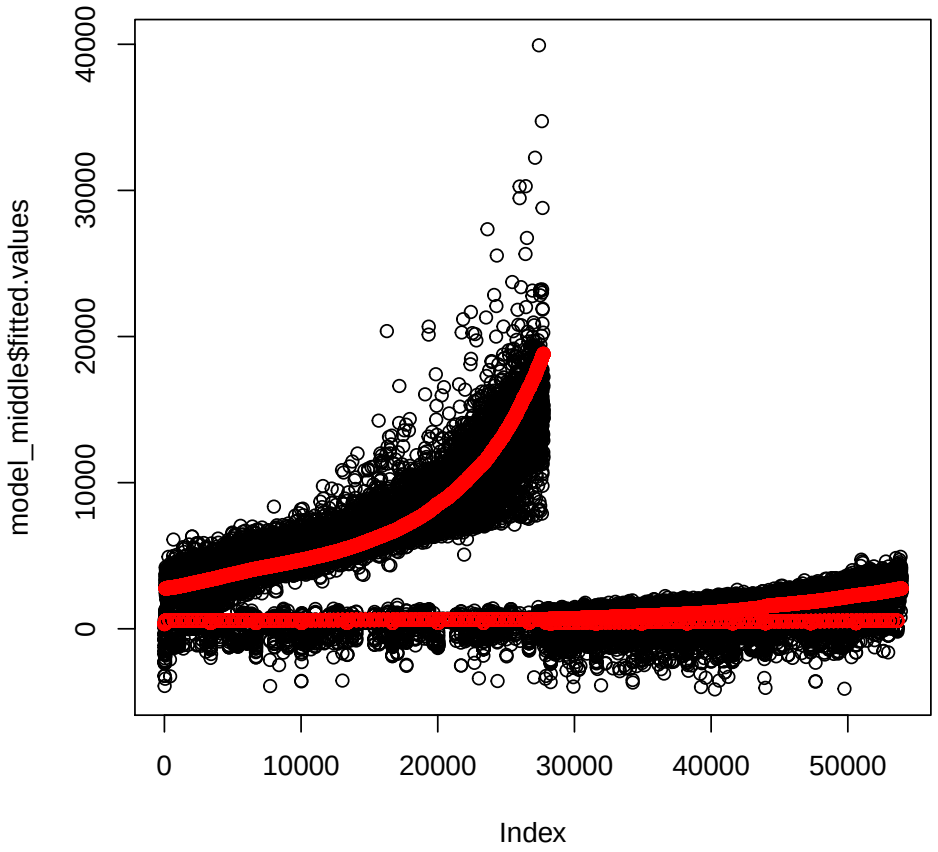
4.2 Additional categorical variables

In case of additional categorical variables we used very similar approach as in continuous variables. But this time we increased maximum number of variables to 4 and considered Gaussian family. The best model we have found is:

$$\text{cost} = -1016.9x + 11192.5\text{carat} + C_i + D_i - 2826.4, \tag{2}$$

color(C_i)	E	F	G	H	I	J
coefficient	-214.2	-282.6	-486.8	-993.2	-1477.5	-2397.4

clarity(D_i)	IF	SI1	SI2	VS1	VS2	VVS1	VVS2
coefficient	5707.1	3922.3	2952.6	4878.2	4559.3	5339.5	5266.3



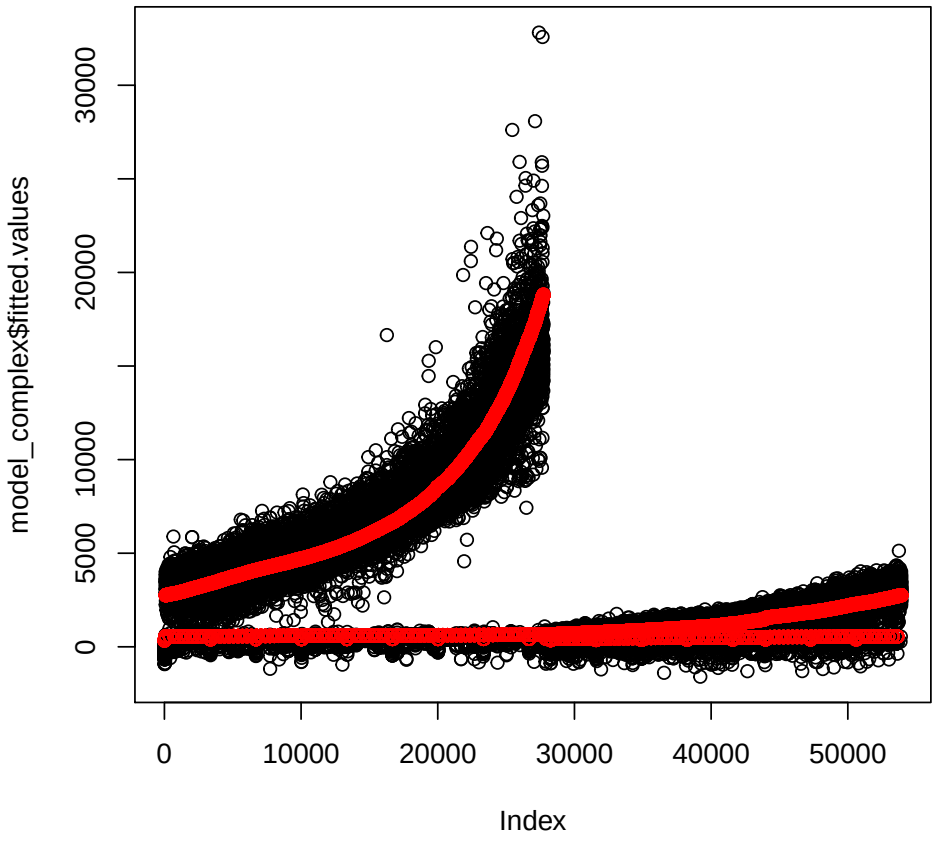
4.3 Model with additional interactions

To find model with additional interactions we use very similar approach as in previous cases. Maximum number of variables is 4 and the family is Gaussian. That's how we find the following model:

$$\text{cost} = -6912.8\text{carat} + 1527.5\text{carat} \cdot x + C_i + D_i - 783.9, \tag{3}$$

carat $\cdot$ color(C_i)	E	F	G	H	I	J
coefficient	-219.1	-342.1	-737.5	-1373.5	-1920.8	-2786.8

carat · clarity(D_i)	IF	SI1	SI2	VS1	VS2	VVS1	VVS2
coefficient	6891.3	3657.7	2664.9	4883.4	4448.8	6154.9	5788.6



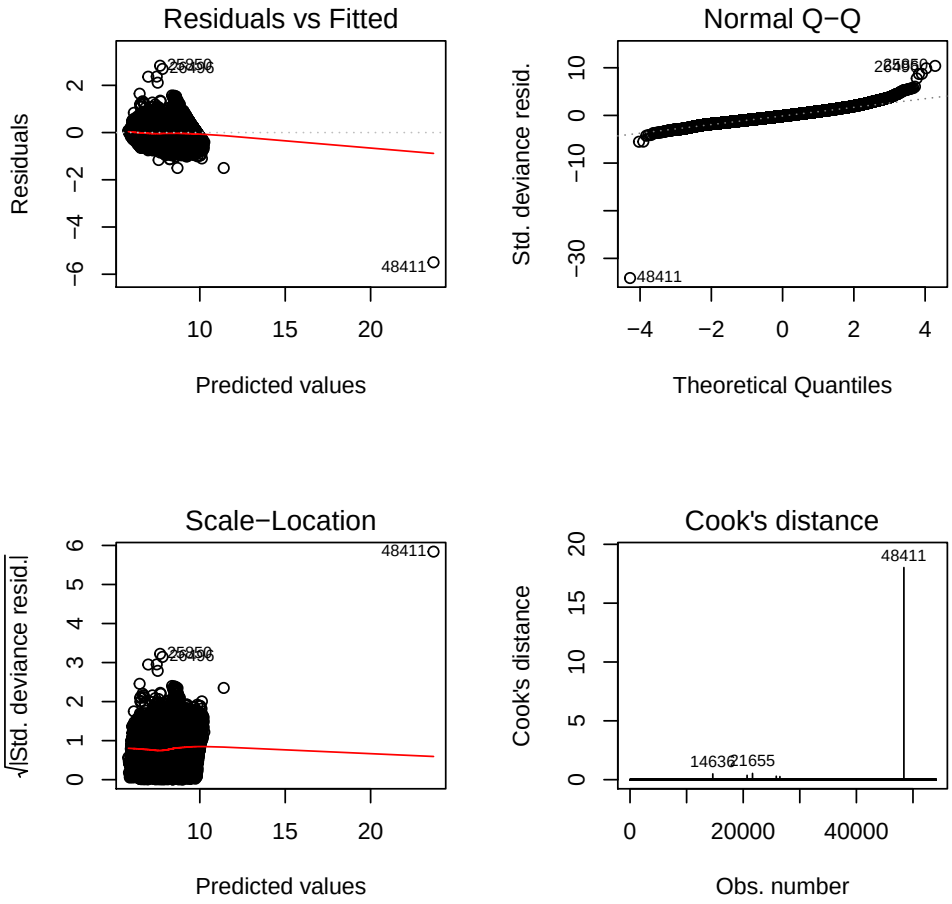
5 Other models

To find those three models from previous section we used glmulti function from glmulti package. Thus we take into consideration all models with specific restrictions. We set maximum model size to 3 in case with only continious variables and to 4 in the rest of cases.

We used glmulti function to find all of considered models. But it turned out, that in second and third case the best model doesn't include z variable. That arouse our curiosity if model excluding this variable is significantly better than with it. Under BIC criteria best model with categorical variables with additional z is only 0.02 % better than without it. Although it gives better BIC it contains more variables so it may be considered as worse model.

6 Check model assumptions

We checked if fitted models fulfill appropriate assumptions. It turns out that none of them do, but we will assume that they do. On the plots below we can see that non of them has normally distributed residuals. Chart 'Residuals vs Fitted' present the distribution of residuals which should be placed around 0. In each of our model the assumption about homogenity is not meet.The normal Q-Q shows if your residuals are normally distributed. Residuals should go around the diagonal line but in ur cases they are not. Cook's distance for residuals helps to detect outliers. They are visible in our cases and we try to handle them in next step of our analysis. Scale location - to describe!!!!! [Tu bym chciała, żeby pojawiły się tylko wykresy o kótrych wspom-



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7 Outliers handling

To find Outliers of our fits we use outlierTest function. It provides us a list of most significant outliers. We decided to delete outliers that are too far from rest of the data. This decision was made because of the fact that this observations are much different then others in only choosen characterisics and it could be the mistake. After that we can try to fit the models again (three lines below but using dataset with deleted outliers - different for each glm or fit by glmulti again, but maybe not necessarily).

	number of variables	AIC	difference between the model and the best model
Model with only continous variables without outliers	3	848300	0.0%
Model with only continous variables with outliers	3	848800	-0.06%
Model with continous and categorical variables	4	912700	-7.6%
Model with interactions	4	884100	-4.2%

8 Order models

It turns out that the best fit we managed to make is with the simplest model with just continuous variables. It becomes even better when we delete outliers. The worst fit of those three models was obtained for model with continuous and categorical variables, but without interactions. The most complex model with additional interactions gave fit somewhere between two previous ones.

9 Check significance of parameters

To check if all parameters in our models are significant we use function summary called at the best model that we find. Than we look at the significance codes and we can find out what parameters are significant. The all summaries are shown below:

```
> summary(model_simple_out)

Call:
glm(formula = price ~ z + x + carat, family = Gamma(link = "log"),
    data = diamonds_data_omited_simplout)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.4945  -0.1971  -0.0367   0.1362   2.8305

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.088645   0.019882   54.76   <2e-16 ***
z            0.571280   0.007689   74.30   <2e-16 ***
x            0.971664   0.006364  152.69   <2e-16 ***
carat       -1.077577   0.011994  -89.85   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.07442222)

    Null deviance: 52790.7  on 53889  degrees of freedom
Residual deviance:  3696.1  on 53886  degrees of freedom
AIC: 848304

Number of Fisher Scoring iterations: 16

> summary(model_middle)

Call:
glm(formula = price ~ color + clarity + x + carat, family = gaussian(),
    data = diamonds_data_omited)
```

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-21911.2    -592.4    -177.9     383.6   10661.4

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -2826.45      93.97  -30.08   <2e-16 ***
colorE       -214.17      18.14  -11.80   <2e-16 ***
colorF       -282.59      18.35  -15.40   <2e-16 ***
colorG       -486.83      17.96  -27.11   <2e-16 ***
colorH       -993.16      19.09  -52.02   <2e-16 ***
colorI      -1477.46      21.46  -68.83   <2e-16 ***
colorJ      -2397.39      26.50  -90.46   <2e-16 ***
clarityIF    5707.09      51.01  111.89   <2e-16 ***
claritySI1   3922.27      43.75   89.66   <2e-16 ***
claritySI2   2952.57      44.01   67.09   <2e-16 ***
clarityVS1   4878.18      44.59  109.41   <2e-16 ***
clarityVS2   4559.32      43.90  103.86   <2e-16 ***
clarityVVS1  5339.55      47.12  113.31   <2e-16 ***
clarityVVS2  5266.32      45.85  114.87   <2e-16 ***
x           -1016.88      21.46  -47.38   <2e-16 ***
carat       11192.46      50.74  220.59   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 1313862)

    Null deviance: 8.5723e+11  on 53919  degrees of freedom
Residual deviance: 7.0822e+10  on 53904  degrees of freedom
AIC: 912687

Number of Fisher Scoring iterations: 2
```

```
> summary(model_complex)

Call:
glm(formula = price ~ carat + carat:x + carat:color + carat:clarity,
    family = gaussian(), data = diamonds_data_omited)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-14794.9    -401.1     -26.9     332.4    8974.6

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       -783.901     17.108  -45.82   <2e-16 ***
carat            -6912.758     86.359  -80.05   <2e-16 ***
carat:x           1527.515      9.482  161.10   <2e-16 ***
carat:colorE      -219.073     18.503  -11.84   <2e-16 ***
carat:colorF      -342.142     17.934  -19.08   <2e-16 ***
carat:colorG      -737.484     17.290  -42.65   <2e-16 ***
carat:colorH     -1373.460     17.299  -79.40   <2e-16 ***
```

```
carat:colorI      -1920.826     18.141 -105.89   <2e-16 ***
carat:colorJ      -2786.799     19.940 -139.76   <2e-16 ***
carat:clarityIF    6891.256     42.282  162.98   <2e-16 ***
carat:claritySI1   3657.671     24.449  149.61   <2e-16 ***
carat:claritySI2   2664.851     24.041  110.84   <2e-16 ***
carat:clarityVS1   4883.444     25.999  187.83   <2e-16 ***
carat:clarityVS2   4448.760     24.833  179.15   <2e-16 ***
carat:clarityVVS1  6154.864     34.457  178.62   <2e-16 ***
carat:clarityVVS2  5788.636     29.482  196.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 773362.4)

    Null deviance: 8.5723e+11  on 53919  degrees of freedom
Residual deviance: 4.1687e+10  on 53904  degrees of freedom
AIC: 884111

Number of Fisher Scoring iterations: 2
```

For two other models we do the same analysis. It turns out that in all models that were fitted by us all parameters are significant. It means that we shouldn't get rid of them.

10 Conclusions