МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ
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Факультет «Информатика и системы управления»
Кафедра «Систем обработки информации и управления»

ОТЧЕТ

Лабораторная работа №__2__
по дисциплине «Методы машинного обучения»

ИСПОЛНИТЕЛЬ: _Морозенков О.Н___
ФИО
группа ИУ5-23М _____
подпись
"__"_____2022 г.

ПРЕПОДАВАТЕЛЬ: _Гапанюк Ю.Е._____
ФИО
_____
подпись
"__"_____2022 г.

Москва - 2022

Цель лабораторной работы: изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

Задание:

1. Выбрать набор данных (датасет), содержащий категориальные и числовые признаки и пропуски в данных. Для выполнения следующих пунктов можно использовать несколько различных наборов данных (один для обработки пропусков, другой для категориальных признаков и т.д.) Просьба не использовать датасет, на котором данная задача решалась в лекции.
2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
    i. устранение пропусков в данных;
    ii. кодирование категориальных признаков;
    iii. нормализацию числовых признаков.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats

data = pd.read_csv("./house_sales.csv")

data = data.drop('Id', 1)
data.head()
```

```
/tmp/ipykernel_1499671/222650945.py:1: FutureWarning: In a future version of
pandas all arguments of DataFrame.drop except for the argument 'labels' will
be keyword-only.
  data = data.drop('Id', 1)
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	\
0	60	RL	65.0	8450	Pave	NaN	Reg	
1	20	RL	80.0	9600	Pave	NaN	Reg	
2	60	RL	68.0	11250	Pave	NaN	IR1	
3	70	RL	60.0	9550	Pave	NaN	IR1	
4	60	RL	84.0	14260	Pave	NaN	IR1	

	LandContour	Utilities	LotConfig	...	PoolArea	PoolQC	Fence	MiscFeature	\
0	Lvl	AllPub	Inside	...	0	NaN	NaN	NaN	
1	Lvl	AllPub	FR2	...	0	NaN	NaN	NaN	
2	Lvl	AllPub	Inside	...	0	NaN	NaN	NaN	
3	Lvl	AllPub	Corner	...	0	NaN	NaN	NaN	
4	Lvl	AllPub	FR2	...	0	NaN	NaN	NaN	

	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	0	2	2008	WD	Normal	208500
1	0	5	2007	WD	Normal	181500
2	0	9	2008	WD	Normal	223500
3	0	2	2006	WD	Abnorml	140000
4	0	12	2008	WD	Normal	250000

[5 rows x 80 columns]

```
data_features = list(zip(
# признаки
[i for i in data.columns],
zip(
    # типы колонок
    [str(i) for i in data.dtypes],
    # проверим есть ли пропущенные значения
    [i for i in data.isnull().sum()]
)))
# Признаки с типом данных и количеством пропусков
data_features
```

```
[('MSSubClass', ('int64', 0)),
 ('MSZoning', ('object', 0)),
 ('LotFrontage', ('float64', 259)),
 ('LotArea', ('int64', 0)),
 ('Street', ('object', 0)),
 ('Alley', ('object', 1369)),
 ('LotShape', ('object', 0)),
 ('LandContour', ('object', 0)),
 ('Utilities', ('object', 0)),
 ('LotConfig', ('object', 0)),
 ('LandSlope', ('object', 0)),
 ('Neighborhood', ('object', 0)),
 ('Condition1', ('object', 0)),
 ('Condition2', ('object', 0)),
 ('BldgType', ('object', 0)),
 ('HouseStyle', ('object', 0)),
 ('OverallQual', ('int64', 0)),
 ('OverallCond', ('int64', 0)),
 ('YearBuilt', ('int64', 0)),
 ('YearRemodAdd', ('int64', 0)),
 ('RoofStyle', ('object', 0)),
 ('RoofMatl', ('object', 0)),
 ('Exterior1st', ('object', 0)),
 ('Exterior2nd', ('object', 0)),
 ('MasVnrType', ('object', 8)),
 ('MasVnrArea', ('float64', 8)),
 ('ExterQual', ('object', 0)),
 ('ExterCond', ('object', 0)),
 ('Foundation', ('object', 0)),
 ('BsmtQual', ('object', 37)),
 ('BsmtCond', ('object', 37)),
 ('BsmtExposure', ('object', 38)),
 ('BsmtFinType1', ('object', 37)),
 ('BsmtFinSF1', ('int64', 0)),
 ('BsmtFinType2', ('object', 38)),
 ('BsmtFinSF2', ('int64', 0)),
 ('BsmtUnfSF', ('int64', 0)),
 ('TotalBsmtSF', ('int64', 0)),
 ('Heating', ('object', 0)),
 ('HeatingQC', ('object', 0)),
 ('CentralAir', ('object', 0)),
 ('Electrical', ('object', 1)),
 ('1stFlrSF', ('int64', 0)),
 ('2ndFlrSF', ('int64', 0)),
 ('LowQualFinSF', ('int64', 0)),
 ('GrLivArea', ('int64', 0)),
 ('BsmtFullBath', ('int64', 0)),
 ('BsmtHalfBath', ('int64', 0)),
 ('FullBath', ('int64', 0)),
 ('HalfBath', ('int64', 0)),
```

```
 ('BedroomAbvGr', ('int64', 0)),
 ('KitchenAbvGr', ('int64', 0)),
 ('KitchenQual', ('object', 0)),
 ('TotRmsAbvGrd', ('int64', 0)),
 ('Functional', ('object', 0)),
 ('Fireplaces', ('int64', 0)),
 ('FireplaceQu', ('object', 690)),
 ('GarageType', ('object', 81)),
 ('GarageYrBlt', ('float64', 81)),
 ('GarageFinish', ('object', 81)),
 ('GarageCars', ('int64', 0)),
 ('GarageArea', ('int64', 0)),
 ('GarageQual', ('object', 81)),
 ('GarageCond', ('object', 81)),
 ('PavedDrive', ('object', 0)),
 ('WoodDeckSF', ('int64', 0)),
 ('OpenPorchSF', ('int64', 0)),
 ('EnclosedPorch', ('int64', 0)),
 ('3SsnPorch', ('int64', 0)),
 ('ScreenPorch', ('int64', 0)),
 ('PoolArea', ('int64', 0)),
 ('PoolQC', ('object', 1453)),
 ('Fence', ('object', 1179)),
 ('MiscFeature', ('object', 1406)),
 ('MiscVal', ('int64', 0)),
 ('MoSold', ('int64', 0)),
 ('YrSold', ('int64', 0)),
 ('SaleType', ('object', 0)),
 ('SaleCondition', ('object', 0)),
 ('SalePrice', ('int64', 0))]
```

Устранение пропусков

```
# Доля (процент) пропусков
[(c, data[c].isnull().mean()) for c in data.columns]
```

```
[('MSSubClass', 0.0),
 ('MSZoning', 0.0),
 ('LotFrontage', 0.1773972602739726),
 ('LotArea', 0.0),
 ('Street', 0.0),
 ('Alley', 0.9376712328767123),
 ('LotShape', 0.0),
 ('LandContour', 0.0),
 ('Utilities', 0.0),
 ('LotConfig', 0.0),
 ('LandSlope', 0.0),
 ('Neighborhood', 0.0),
 ('Condition1', 0.0),
 ('Condition2', 0.0),
 ('BldgType', 0.0),
```

('HouseStyle', 0.0),
('OverallQual', 0.0),
('OverallCond', 0.0),
('YearBuilt', 0.0),
('YearRemodAdd', 0.0),
('RoofStyle', 0.0),
('RoofMatl', 0.0),
('Exterior1st', 0.0),
('Exterior2nd', 0.0),
('MasVnrType', 0.005479452054794521),
('MasVnrArea', 0.005479452054794521),
('ExterQual', 0.0),
('ExterCond', 0.0),
('Foundation', 0.0),
('BsmtQual', 0.025342465753424658),
('BsmtCond', 0.025342465753424658),
('BsmtExposure', 0.026027397260273973),
('BsmtFinType1', 0.025342465753424658),
('BsmtFinSF1', 0.0),
('BsmtFinType2', 0.026027397260273973),
('BsmtFinSF2', 0.0),
('BsmtUnfSF', 0.0),
('TotalBsmtSF', 0.0),
('Heating', 0.0),
('HeatingQC', 0.0),
('CentralAir', 0.0),
('Electrical', 0.0006849315068493151),
('1stFlrSF', 0.0),
('2ndFlrSF', 0.0),
('LowQualFinSF', 0.0),
('GrLivArea', 0.0),
('BsmtFullBath', 0.0),
('BsmtHalfBath', 0.0),
('FullBath', 0.0),
('HalfBath', 0.0),
('BedroomAbvGr', 0.0),
('KitchenAbvGr', 0.0),
('KitchenQual', 0.0),
('TotRmsAbvGrd', 0.0),
('Functional', 0.0),
('Fireplaces', 0.0),
('FireplaceQu', 0.4726027397260274),
('GarageType', 0.05547945205479452),
('GarageYrBlt', 0.05547945205479452),
('GarageFinish', 0.05547945205479452),
('GarageCars', 0.0),
('GarageArea', 0.0),
('GarageQual', 0.05547945205479452),
('GarageCond', 0.05547945205479452),
('PavedDrive', 0.0),

```
 ('WoodDeckSF', 0.0),
 ('OpenPorchSF', 0.0),
 ('EnclosedPorch', 0.0),
 ('3SsnPorch', 0.0),
 ('ScreenPorch', 0.0),
 ('PoolArea', 0.0),
 ('PoolQC', 0.9952054794520548),
 ('Fence', 0.8075342465753425),
 ('MiscFeature', 0.963013698630137),
 ('MiscVal', 0.0),
 ('MoSold', 0.0),
 ('YrSold', 0.0),
 ('SaleType', 0.0),
 ('SaleCondition', 0.0),
 ('SalePrice', 0.0)]
```

```
# Удаление колонок, содержащих пустые значения
data.dropna(axis=1, how='any')
```

```
      MSSubClass MSZoning  LotArea Street LotShape LandContour Utilities  \
0             60       RL     8450   Pave      Reg         Lvl    AllPub
1             20       RL     9600   Pave      Reg         Lvl    AllPub
2             60       RL    11250   Pave      IR1         Lvl    AllPub
3             70       RL     9550   Pave      IR1         Lvl    AllPub
4             60       RL    14260   Pave      IR1         Lvl    AllPub
...          ...      ...      ...    ...      ...         ...       ...
1455          60       RL     7917   Pave      Reg         Lvl    AllPub
1456          20       RL    13175   Pave      Reg         Lvl    AllPub
1457          70       RL     9042   Pave      Reg         Lvl    AllPub
1458          20       RL     9717   Pave      Reg         Lvl    AllPub
1459          20       RL     9937   Pave      Reg         Lvl    AllPub

     LotConfig LandSlope Neighborhood  ... EnclosedPorch 3SsnPorch  \
0       Inside       Gtl      CollgCr  ...             0         0
1          FR2       Gtl      Veenker  ...             0         0
2       Inside       Gtl      CollgCr  ...             0         0
3       Corner       Gtl      Crawfor  ...           272         0
4          FR2       Gtl      NoRidge  ...             0         0
...        ...       ...          ...  ...           ...       ...
1455    Inside       Gtl      Gilbert  ...             0         0
1456    Inside       Gtl       NWAmes  ...             0         0
1457    Inside       Gtl      Crawfor  ...             0         0
1458    Inside       Gtl        NAmes  ...           112         0
1459    Inside       Gtl      Edwards  ...             0         0

     ScreenPorch PoolArea  MiscVal  MoSold  YrSold  SaleType SaleCondition  \
0              0        0        0       2    2008        WD        Normal
1              0        0        0       5    2007        WD        Normal
2              0        0        0       9    2008        WD        Normal
3              0        0        0       2    2006        WD       Abnorml
```

```
4              0        0        0      12    2008        WD        Normal
...          ...      ...      ...     ...     ...       ...           ...
1455           0        0        0       8    2007        WD        Normal
1456           0        0        0       2    2010        WD        Normal
1457           0        0     2500       5    2010        WD        Normal
1458           0        0        0       4    2010        WD        Normal
1459           0        0        0       6    2008        WD        Normal

     SalePrice
0       208500
1       181500
2       223500
3       140000
4       250000
...        ...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500

[1460 rows x 61 columns]
```

```
# Удаление колонок, содержащих пустые значения
data.dropna(axis=1, how='any')
```

```
      MSSubClass MSZoning  LotArea Street LotShape LandContour Utilities  \
0             60       RL     8450   Pave      Reg         Lvl    AllPub
1             20       RL     9600   Pave      Reg         Lvl    AllPub
2             60       RL    11250   Pave      IR1         Lvl    AllPub
3             70       RL     9550   Pave      IR1         Lvl    AllPub
4             60       RL    14260   Pave      IR1         Lvl    AllPub
...          ...      ...      ...    ...      ...         ...       ...
1455          60       RL     7917   Pave      Reg         Lvl    AllPub
1456          20       RL    13175   Pave      Reg         Lvl    AllPub
1457          70       RL     9042   Pave      Reg         Lvl    AllPub
1458          20       RL     9717   Pave      Reg         Lvl    AllPub
1459          20       RL     9937   Pave      Reg         Lvl    AllPub

     LotConfig LandSlope Neighborhood  ... EnclosedPorch 3SsnPorch  \
0       Inside       Gtl      CollgCr  ...             0         0
1          FR2       Gtl      Veenker  ...             0         0
2       Inside       Gtl      CollgCr  ...             0         0
3       Corner       Gtl      Crawfor  ...           272         0
4          FR2       Gtl      NoRidge  ...             0         0
...        ...       ...          ...  ...           ...       ...
1455    Inside       Gtl      Gilbert  ...             0         0
1456    Inside       Gtl       NWAmes  ...             0         0
1457    Inside       Gtl      Crawfor  ...             0         0
1458    Inside       Gtl        NAmes  ...           112         0
```

```
1459    Inside       Gtl      Edwards  ...             0         0

     ScreenPorch PoolArea  MiscVal  MoSold  YrSold  SaleType SaleCondition  \
0              0        0        0       2    2008        WD        Normal
1              0        0        0       5    2007        WD        Normal
2              0        0        0       9    2008        WD        Normal
3              0        0        0       2    2006        WD       Abnorml
4              0        0        0      12    2008        WD        Normal
...          ...      ...      ...     ...     ...       ...           ...
1455           0        0        0       8    2007        WD        Normal
1456           0        0        0       2    2010        WD        Normal
1457           0        0     2500       5    2010        WD        Normal
1458           0        0        0       4    2010        WD        Normal
1459           0        0        0       6    2008        WD        Normal

     SalePrice
0       208500
1       181500
2       223500
3       140000
4       250000
...        ...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500

[1460 rows x 61 columns]
```

```
# Удаление колонок с высоким процентом пропусков (более 50%)
data.dropna(axis=1, thresh=730)
```

```
      MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour
\
0             60       RL         65.0     8450   Pave      Reg         Lvl
1             20       RL         80.0     9600   Pave      Reg         Lvl
2             60       RL         68.0    11250   Pave      IR1         Lvl
3             70       RL         60.0     9550   Pave      IR1         Lvl
4             60       RL         84.0    14260   Pave      IR1         Lvl
...          ...      ...          ...      ...    ...      ...         ...
1455          60       RL         62.0     7917   Pave      Reg         Lvl
1456          20       RL         85.0    13175   Pave      Reg         Lvl
1457          70       RL         66.0     9042   Pave      Reg         Lvl
1458          20       RL         68.0     9717   Pave      Reg         Lvl
1459          20       RL         75.0     9937   Pave      Reg         Lvl

     Utilities LotConfig LandSlope  ... EnclosedPorch 3SsnPorch ScreenPorch
\
0       AllPub    Inside       Gtl  ...             0         0           0
```

```
1       AllPub       FR2       Gtl  ...             0         0           0
2       AllPub    Inside       Gtl  ...             0         0           0
3       AllPub    Corner       Gtl  ...           272         0           0
4       AllPub       FR2       Gtl  ...             0         0           0
...        ...       ...       ...  ...           ...       ...         ...
1455    AllPub    Inside       Gtl  ...             0         0           0
1456    AllPub    Inside       Gtl  ...             0         0           0
1457    AllPub    Inside       Gtl  ...             0         0           0
1458    AllPub    Inside       Gtl  ...           112         0           0
1459    AllPub    Inside       Gtl  ...             0         0           0

     PoolArea MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0           0       0       2    2008        WD         Normal    208500
1           0       0       5    2007        WD         Normal    181500
2           0       0       9    2008        WD         Normal    223500
3           0       0       2    2006        WD        Abnorml    140000
4           0       0      12    2008        WD         Normal    250000
...       ...     ...     ...     ...       ...            ...       ...
1455        0       0       8    2007        WD         Normal    175000
1456        0       0       2    2010        WD         Normal    210000
1457        0    2500       5    2010        WD         Normal    266500
1458        0       0       4    2010        WD         Normal    142125
1459        0       0       6    2008        WD         Normal    147500

[1460 rows x 76 columns]
```

```python
# Заполним пропуски возраста средними значениями
def impute_na(df, variable, value):
    df[variable].fillna(value, inplace=True)
impute_na(data, 'LotFrontage', data['LotFrontage'].mean())

# Убедимся, что признак LotFrontage не имеет пустых значений
data.isnull().sum()
```

```
MSSubClass       0
MSZoning         0
LotFrontage      0
LotArea          0
Street           0
                ..
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 80, dtype: int64
```

Кодирование категориальных признаков

```python
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
cat_enc_le = le.fit_transform(data['SaleCondition'])

data['SaleCondition'].unique()

array(['Normal', 'Abnorml', 'Partial', 'AdjLand', 'Alloca', 'Family'],
      dtype=object)

np.unique(cat_enc_le)

array([0, 1, 2, 3, 4, 5])

le.inverse_transform([0, 1, 2, 3, 4, 5])

array(['Abnorml', 'AdjLand', 'Alloca', 'Family', 'Normal', 'Partial'],
      dtype=object)

data['LotConfig'].unique()

array(['Inside', 'FR2', 'Corner', 'CulDSac', 'FR3'], dtype=object)

#CountEncoder
from category_encoders.count import CountEncoder as ce_CountEncoder

ce_CountEncoder1 = ce_CountEncoder()
data_COUNT_ENC =
ce_CountEncoder1.fit_transform(data[data.columns.difference(['SaleType'])])

data_COUNT_ENC.head()
```

	1stFlrSF	2ndFlrSF	3SsnPorch	Alley	BedroomAbvGr	BldgType	BsmtCond	\
0	856	854	0	1369	3	1220	1311	
1	1262	0	0	1369	3	1220	1311	
2	920	866	0	1369	3	1220	1311	
3	961	756	0	1369	3	1220	65	
4	1145	1053	0	1369	4	1220	1311	

	BsmtExposure	BsmtFinSF1	BsmtFinSF2	...	SalePrice	ScreenPorch	Street
\							
0	953	706	0	...	208500	0	1454
1	134	978	0	...	181500	0	1454
2	114	486	0	...	223500	0	1454
3	953	216	0	...	140000	0	1454
4	221	655	0	...	250000	0	1454

	TotRmsAbvGrd	TotalBsmtSF	Utilities	WoodDeckSF	YearBuilt	YearRemodAdd
\						
0	8	856	1459	0	2003	2003
1	6	1262	1459	298	1976	1976
2	6	920	1459	0	2001	2002
3	7	756	1459	0	1915	1970
4	9	1145	1459	192	2000	2000

```
   YrSold
0    2008
1    2007
2    2008
3    2006
4    2008

[5 rows x 79 columns]
```

```
data['MSZoning'].unique()
```

```
array(['RL', 'RM', 'C (all)', 'FV', 'RH'], dtype=object)
```

```
data_COUNT_ENC['MSZoning'].unique()
```

```
array([1151,  218,   10,   65,   16])
```

```
ce_CountEncoder2 = ce_CountEncoder(normalize=True)
data_FREQ_ENC =
ce_CountEncoder2.fit_transform(data[data.columns.difference(['SaleType'])])
```

```
data_FREQ_ENC['MSZoning'].unique()
```

```
array([0.78835616, 0.14931507, 0.00684932, 0.04452055, 0.0109589 ])
```

```
from category_encoders.helmert import HelmertEncoder as ce_HelmertEncoder

#HelmetEncoder
ce_HelmertEncoder1 = ce_HelmertEncoder()
data_HELM_ENC =
ce_HelmertEncoder1.fit_transform(data[data.columns.difference(['SaleType'])],
data['SaleType'])
```

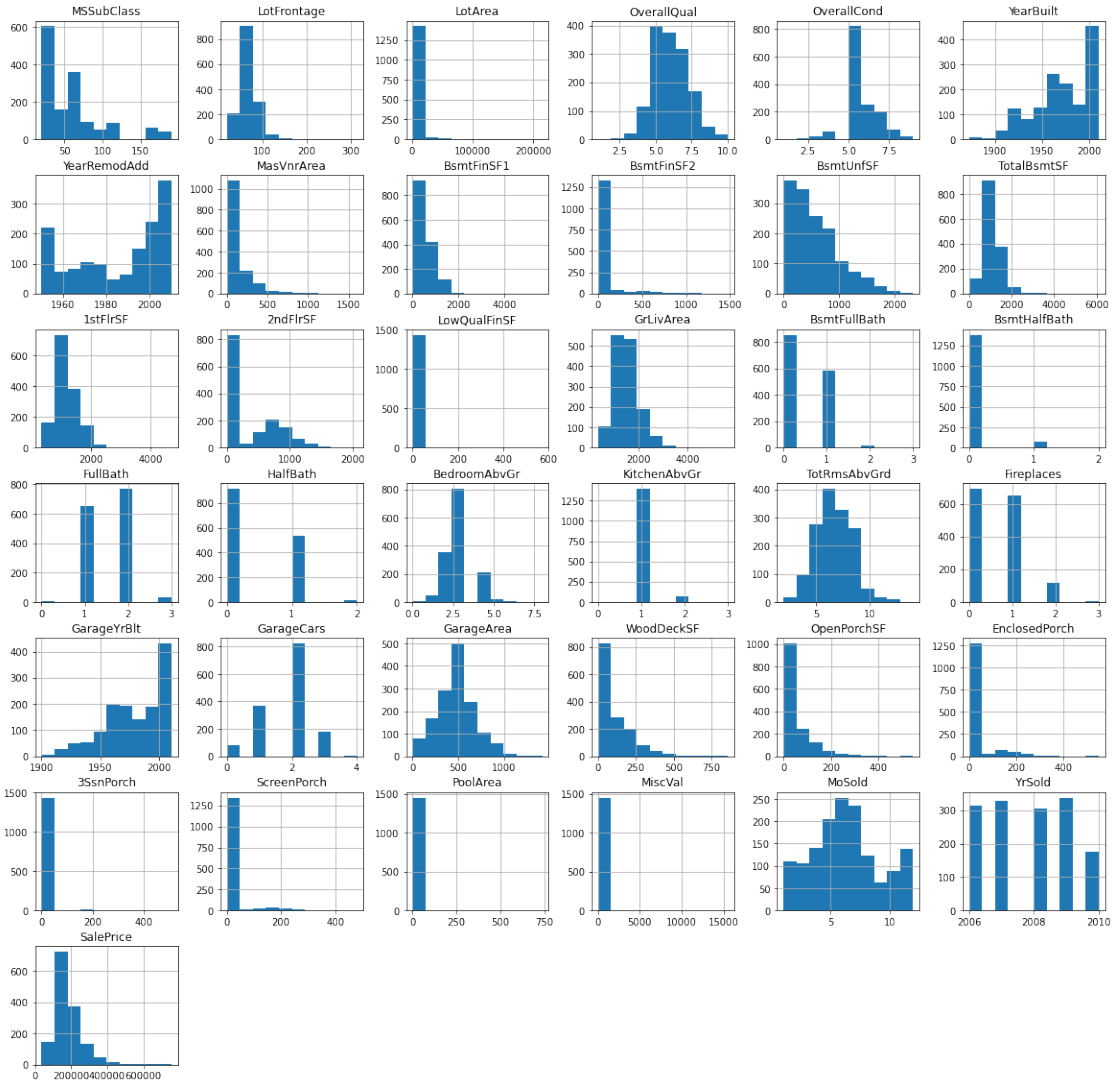
```
data_HELM_ENC.head()
```

```
   intercept  1stFlrSF  2ndFlrSF  3SsnPorch  Alley_0  Alley_1  BedroomAbvGr
\
0          1       856       854          0     -1.0     -1.0             3
1          1      1262         0          0     -1.0     -1.0             3
2          1       920       866          0     -1.0     -1.0             3
3          1       961       756          0     -1.0     -1.0             3
4          1      1145      1053          0     -1.0     -1.0             4

   BldgType_0  BldgType_1  BldgType_2  ...  SalePrice  ScreenPorch  Street_0
\
0        -1.0        -1.0        -1.0  ...     208500            0      -1.0
1        -1.0        -1.0        -1.0  ...     181500            0      -1.0
2        -1.0        -1.0        -1.0  ...     223500            0      -1.0
3        -1.0        -1.0        -1.0  ...     140000            0      -1.0
4        -1.0        -1.0        -1.0  ...     250000            0      -1.0
```

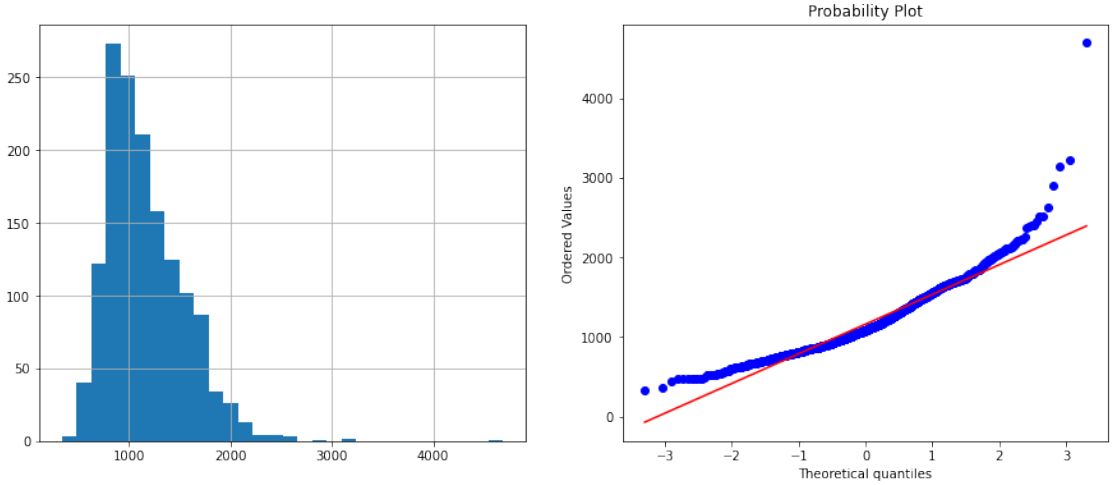
```
   TotRmsAbvGrd  TotalBsmtSF  Utilities_0  WoodDeckSF  YearBuilt  \
0             8          856         -1.0           0       2003
1             6         1262         -1.0         298       1976
2             6          920         -1.0           0       2001
3             7          756         -1.0           0       1915
4             9         1145         -1.0         192       2000

   YearRemodAdd  YrSold
0          2003    2008
1          1976    2007
2          2002    2008
3          1970    2006
4          2000    2008

[5 rows x 255 columns]
```

Нормализация числовых признаков

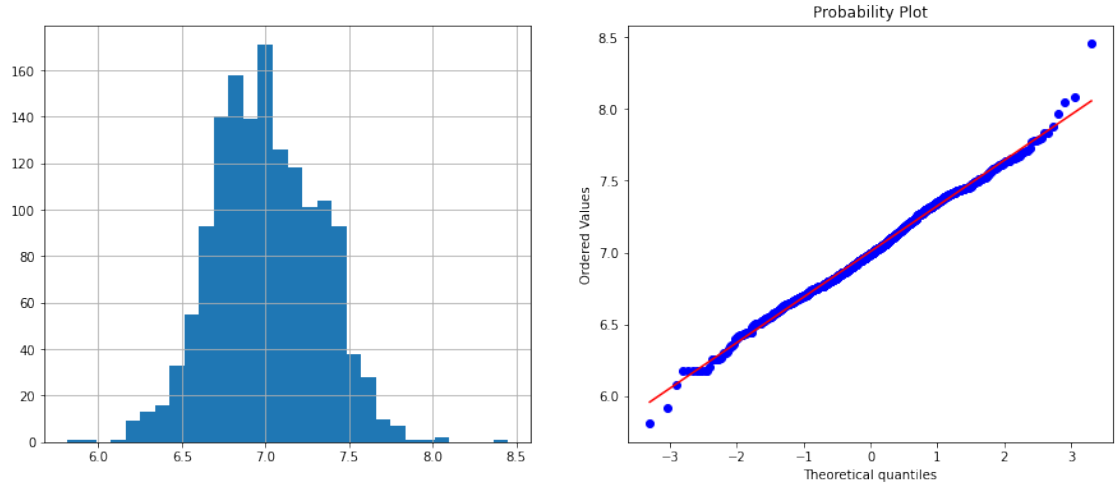
```
def diagnostic_plots(df, variable):
    plt.figure(figsize=(15,6))
    # гистограмма
    plt.subplot(1, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(1, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    plt.show()

data.hist(figsize=(20,20))
plt.show()
```



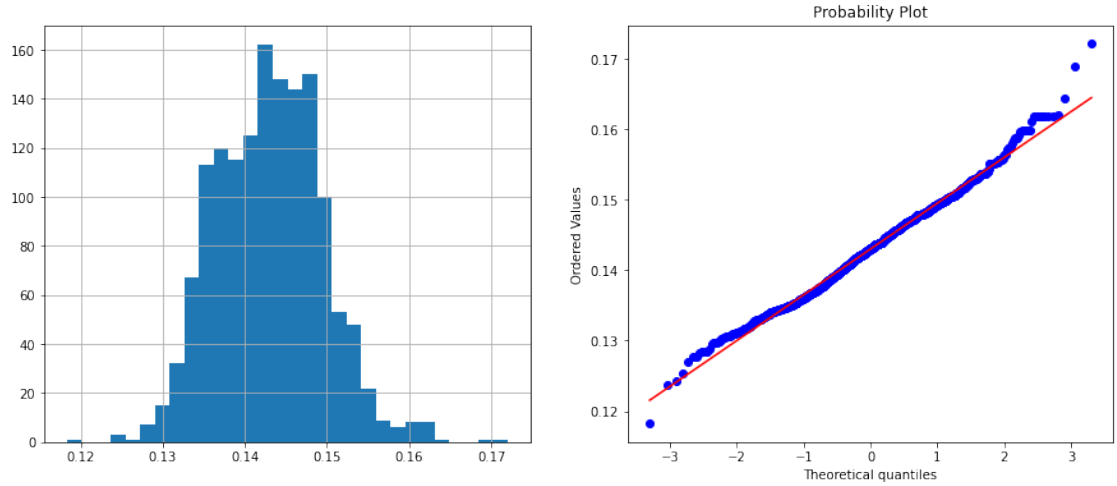

```
diagnostic_plots(data, '1stFlrSF')
```



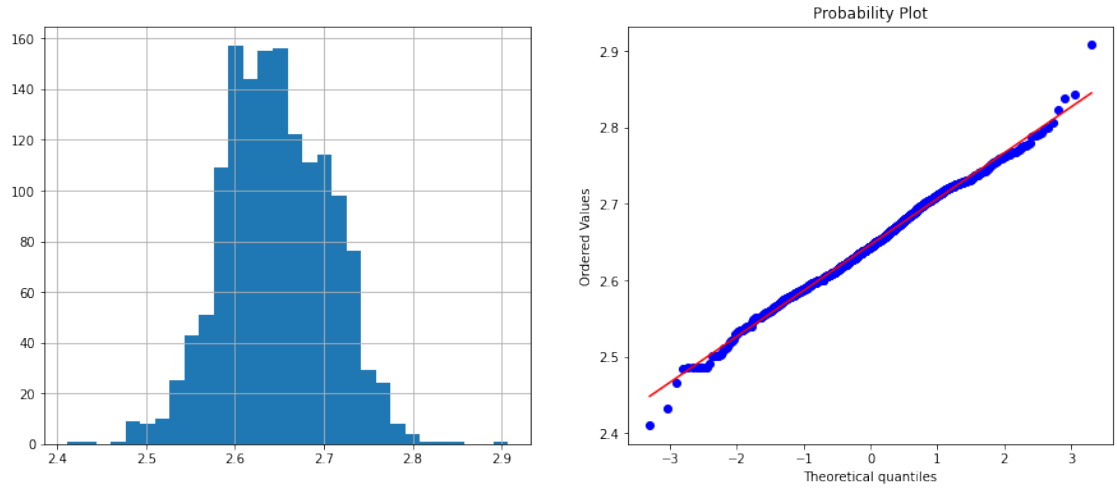
```
#Логарифмическое преобразование
data['1stFlrSF'] = np.log(data['1stFlrSF'])
diagnostic_plots(data, '1stFlrSF')
```



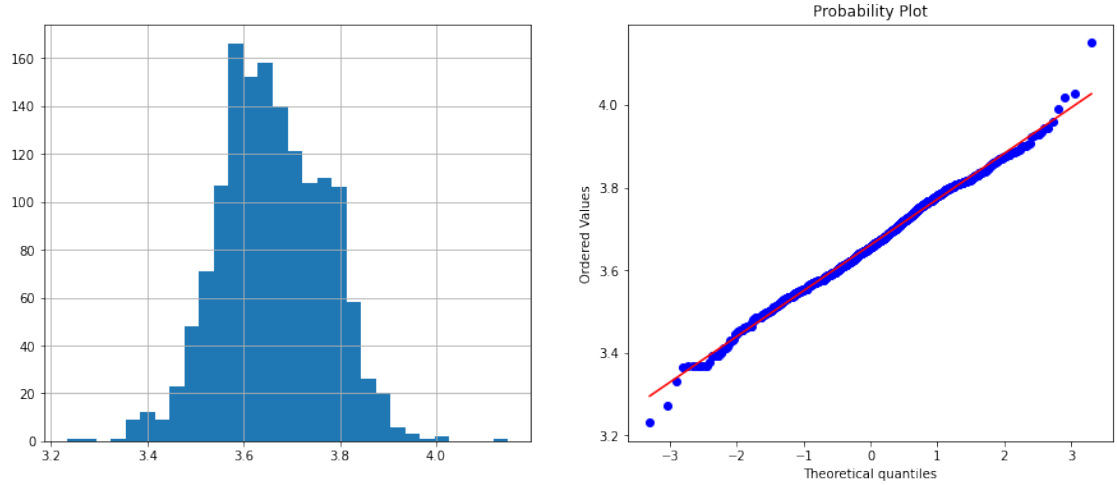

```
#Обратное преобразование
data['1stFlrSF_reciprocal'] = 1 / (data['1stFlrSF'])
diagnostic_plots(data, '1stFlrSF_reciprocal')
```



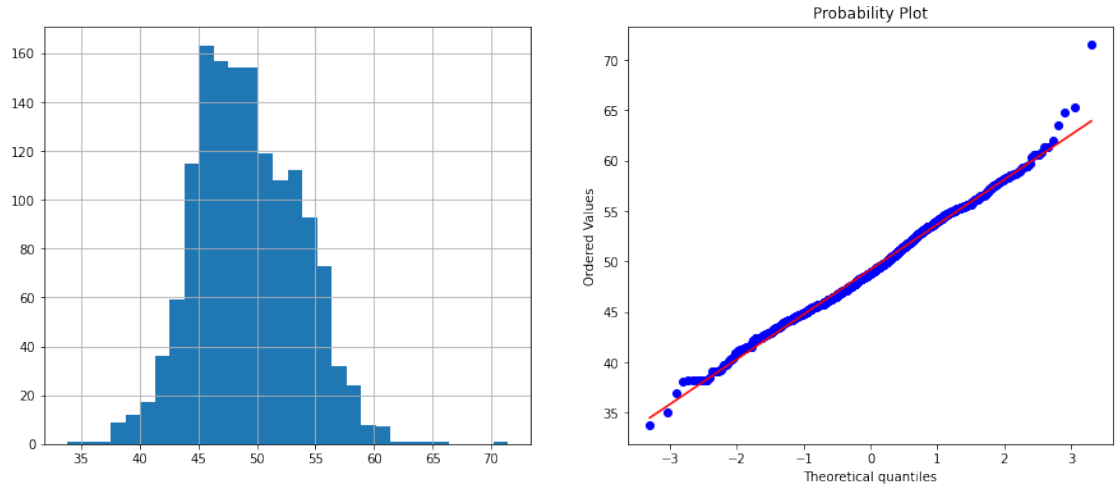

```
#Квадратный корень
data['1stFlrSF_sqr'] = data['1stFlrSF']**(1/2)
diagnostic_plots(data, '1stFlrSF_sqr')
```



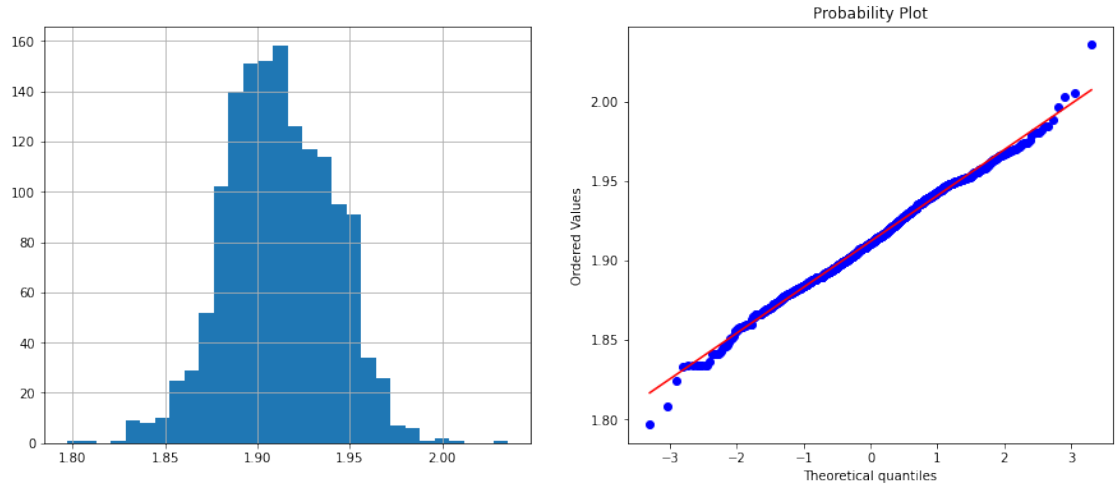

```
#Возведение в степень
data['1stFlrSF_exp1'] = data['1stFlrSF']**(1/1.5)
diagnostic_plots(data, '1stFlrSF_exp1')
```




```
data['1stFlrSF_exp2'] = data['1stFlrSF']**(2)
diagnostic_plots(data, '1stFlrSF_exp2')
```

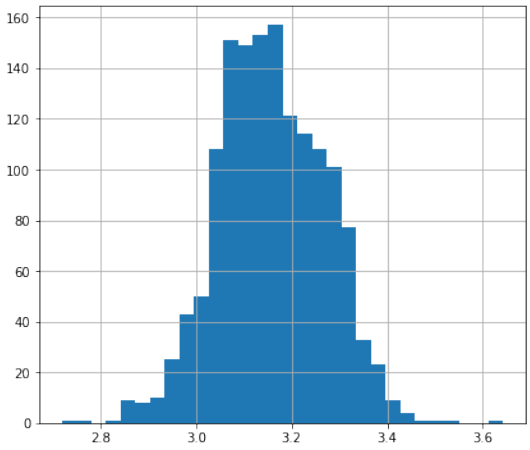


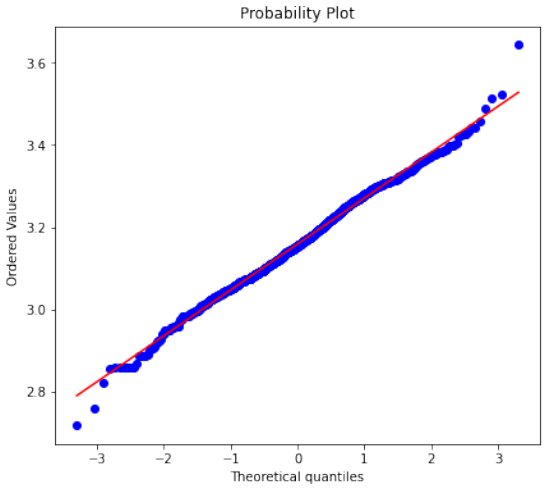

```
data['1stFlrSF_exp3'] = data['1stFlrSF']**(0.333)
diagnostic_plots(data, '1stFlrSF_exp3')
```




```
#Преобразованиея Бокса-Кокса
data['1stFlrSF_boxcox'], param = stats.boxcox(data['1stFlrSF'])
print('Оптимальное значение λ = {}'.format(param))
diagnostic_plots(data, '1stFlrSF_boxcox')
```

```
Оптимальное значение λ = 0.46304765872484194
```


160
140
120
100
80
60
40
20
0
2.8
3.0
3.2
3.4
3.6


Probability Plot
Ordered Values
Theoretical quantiles
3.6
3.4
3.2
3.0
2.8
−3
−2
−1
0
1
2
3