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Лабораторная работа №2

«Обработка признаков (часть 1)»

по дисциплине

«Методы машинного обучения»

ИСПОЛНИТЕЛЬ:

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<u>Цель:</u> Изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

<u>Задание:</u>

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.)

2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
   - устранение пропусков в данных;
   - кодирование категориальных признаков;
   - нормализацию числовых признаков.

Ход выполнения:

This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status. Each row in the data provides relevant information about the patient.

Поля:
id: unique identifier
gender: "Male", "Female" or "Other"
age: age of the patient
hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension
heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart
disease
ever_married: "No" or "Yes"
work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
Residence_type: "Rural" or "Urban"
avg_glucose_level: average glucose level in blood
bmi: body mass index
smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*
stroke: 1 if the patient had a stroke or 0 if not
"Unknown" in smoking_status means that the information is unavailable for this patient

Текст программы:

```
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('/Users/user/Downloads/data_stroke.csv')
```

```
data.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	NaN	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	NaN	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

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

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	Male	NaN	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	Female	NaN	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

```
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
```

```
[('gender', ('object', 0)),
 ('age', ('float64', 16)),
 ('hypertension', ('int64', 0)),
 ('heart_disease', ('int64', 0)),
 ('ever_married', ('object', 0)),
 ('work_type', ('object', 0)),
 ('Residence_type', ('object', 0)),
 ('avg_glucose_level', ('float64', 0)),
 ('bmi', ('float64', 201)),
 ('smoking_status', ('object', 0)),
 ('stroke', ('int64', 0))]
```

Устранение пропусков

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

```
[('gender', 0.0),
 ('age', 0.0031311154598825833),
 ('hypertension', 0.0),
 ('heart_disease', 0.0),
 ('ever_married', 0.0),
 ('work_type', 0.0),
 ('Residence_type', 0.0),
 ('avg_glucose_level', 0.0),
 ('bmi', 0.03933463796477495),
 ('smoking_status', 0.0),
 ('stroke', 0.0)]
```

```
[ ] # Заполним пропуски
    data.dropna(subset=['age'], inplace=True)
```

```
[ ] data['gender'] = data['gender'].astype(str).str[0]
```

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

```
[ ] # Убедимся что нет пустых значений
    data.isnull().sum()
```

```
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

```
[ ] data.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
1	F	61.0	0	0	Yes	Self-employed	Rural	202.21	28.886269	never smoked	1
2	M	80.0	0	1	Yes	Private	Rural	105.92	32.500000	never smoked	1
3	F	49.0	0	0	Yes	Private	Urban	171.23	34.400000	smokes	1
5	M	81.0	0	0	Yes	Private	Urban	186.21	29.000000	formerly smoked	1
6	M	74.0	1	1	Yes	Private	Rural	70.09	27.400000	never smoked	1

Кодирование категориальных признаков

```
[ ] from sklearn.preprocessing import LabelEncoder
```

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

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

    array(['Self-employed', 'Private', 'Govt_job', 'children', 'Never_worked'],
          dtype=object)
```

```
[ ] np.unique(cat_enc_le)

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

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

    array(['Govt_job', 'Never_worked', 'Private', 'Self-employed', 'children'],
          dtype=object)
```

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

    array(['never smoked', 'smokes', 'formerly smoked', 'Unknown'],
          dtype=object)
```

```
[ ] #TargetEncoder
    from category_encoders.target_encoder import TargetEncoder as ce_TargetEncoder
```

```
[ ] ce_TargetEncoder1 = ce_TargetEncoder()
    data_MEAN_ENC = ce_TargetEncoder1.fit_transform(data[data.columns.difference(['stroke'])], data['stroke'])
```

```
[ ] data_MEAN_ENC.head()
```

	Residence_type	age	avg_glucose_level	bmi	ever_married	gender	heart_disease	hypertension	smoking_status	work_type
1	0.044258	61.0	202.21	28.886269	0.063136	0.045896	0	0	0.046178	0.076074
2	0.044258	80.0	105.92	32.500000	0.063136	0.048387	1	0	0.046178	0.048747
3	0.049497	49.0	171.23	34.400000	0.063136	0.045896	0	0	0.052030	0.048747
5	0.049497	81.0	186.21	29.000000	0.063136	0.048387	0	0	0.075000	0.048747
6	0.044258	74.0	70.09	27.400000	0.063136	0.048387	1	1	0.046178	0.048747

```
[ ] def check_mean_encoding(field):
        for s in data[field].unique():
            data_filter = data[data[field]==s]
            if data_filter.shape[0] > 0:
                prob = sum(data_filter['stroke']) / data_filter.shape[0]
                print(s, '-' , prob)
```

```
[ ] check_mean_encoding('gender')

    F - 0.04589614740368509
    M - 0.04838709677419355
    O - 0.0
```

```
[ ] check_mean_encoding('smoking_status')
```

```
never smoked - 0.04617834394904458
smokes - 0.05203045685279188
formerly smoked - 0.075
Unknown - 0.029182879377431907
```

```
[ ] check_mean_encoding('work_type')
```

```
Self-employed - 0.07607361963190185
Private - 0.04874699622382424
Govt_job - 0.0502283105022831
children - 0.002911208151382824
Never_worked - 0.0
```

```
[ ] #Weight of evidence (WoE) encoding
    from category_encoders.woe import WOEEncoder as ce_WOEEncoder
```

```
[ ] ce_WOEEncoder1 = ce_WOEEncoder()
    data_WOE_ENC = ce_WOEEncoder1.fit_transform(data[data.columns.difference(['stroke'])], data['stroke'])
```

```
[ ] data_WOE_ENC.head()
```

	Residence_type	age	avg_glucose_level	bmi	ever_married	gender	heart_disease	hypertension	smoking_status	work_type
1	-0.060512	61.0	202.21	28.886269	0.310539	-0.024090	0	0	-0.013714	0.521122
2	-0.060512	80.0	105.92	32.500000	0.310539	0.033712	1	0	-0.013714	0.038900
3	0.055682	49.0	171.23	34.400000	0.310539	-0.024090	0	0	0.123646	0.038900
5	0.055682	81.0	186.21	29.000000	0.310539	0.033712	0	0	0.504884	0.038900
6	-0.060512	74.0	70.09	27.400000	0.310539	0.033712	1	1	-0.013714	0.038900

```
[ ] def check_woe_encoding(field):
        data_ones = data[data['stroke'] == 1].shape[0]
        data_zeros = data[data['stroke'] == 0].shape[0]

        for s in data[field].unique():
            data_filter = data[data[field]==s]
            if data_filter.shape[0] > 0:

                filter_data_ones = data_filter[data_filter['stroke'] == 1].shape[0]
                filter_data_zeros = data_filter[data_filter['stroke'] == 0].shape[0]

                good = filter_data_ones / data_ones
                bad = filter_data_zeros / data_zeros

                woe = np.log(good/bad)
                print(s, '-' , woe)
```

```
[ ] check_woe_encoding('gender')
```

```
F - -0.023090517909826913
M - 0.032375673556304815
O - -inf
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: RuntimeWarning: divide by zero encountered in log
  from ipykernel import kernelapp as app
```

```
[ ] check_woe_encoding('smoking_status')
```

```
never smoked - -0.01666493933506075
smokes - 0.10880771036540528
formerly smoked - 0.49899520481779985
Unknown - -0.4932550658553942
```

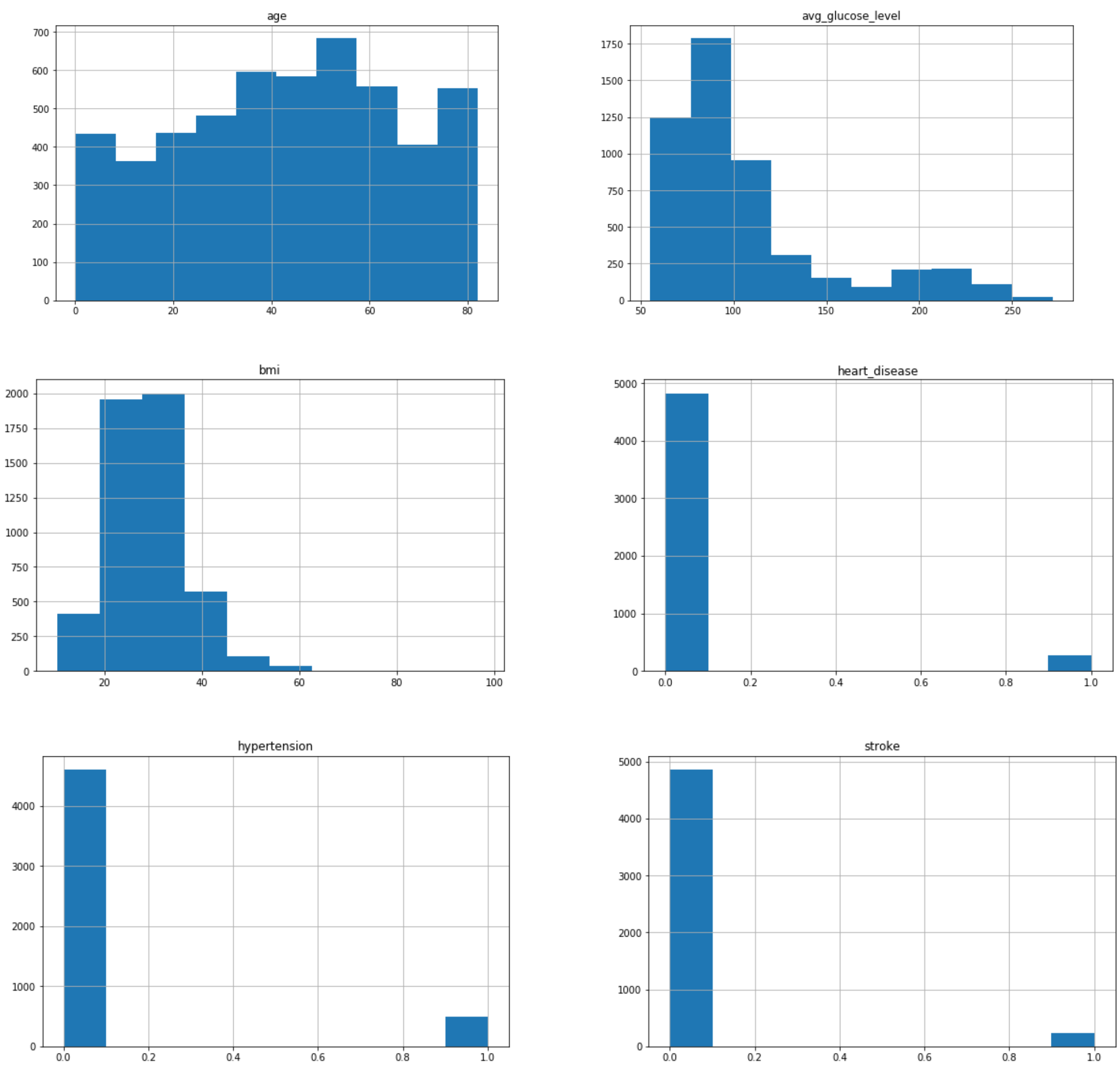
```
[ ] check_woe_encoding('work_type')
```

```
Self-employed - 0.5143699860391127
Private - 0.040164341532197056
Govt_job - 0.07165802189096712
children - -2.8249708289083655
Never_worked - -inf
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: RuntimeWarning: divide by zero encountered in log
  from ipykernel import kernelapp as app
```

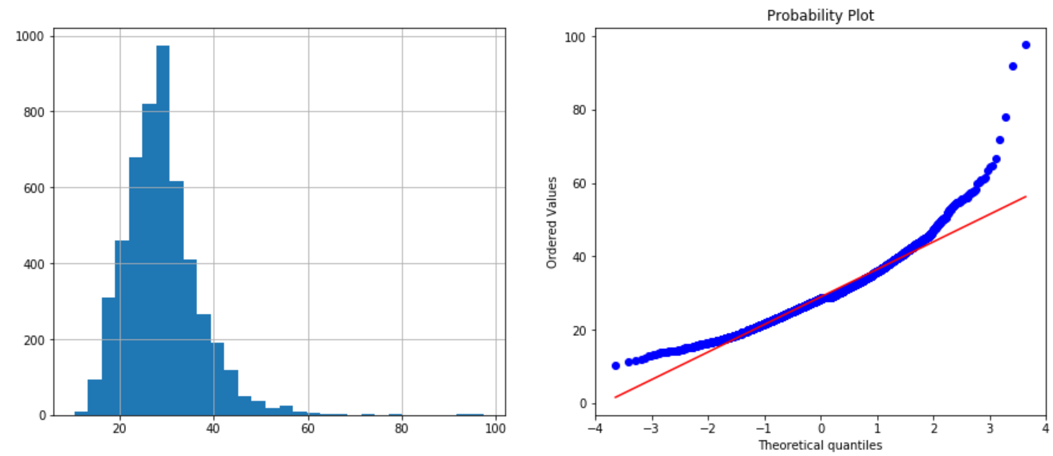
Нормализация числовых признаков

```
[ ] 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()
```

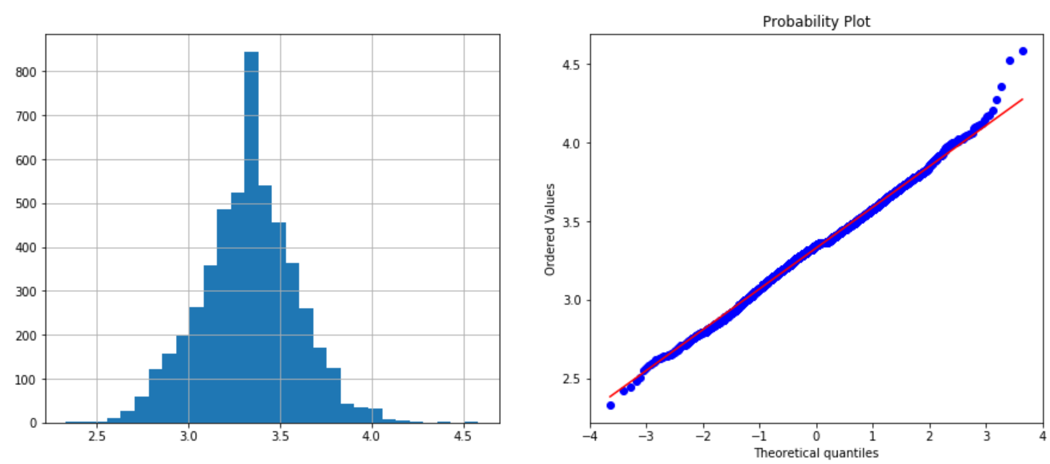
```
[ ] data.hist(figsize=(20,20))
    plt.show()
```



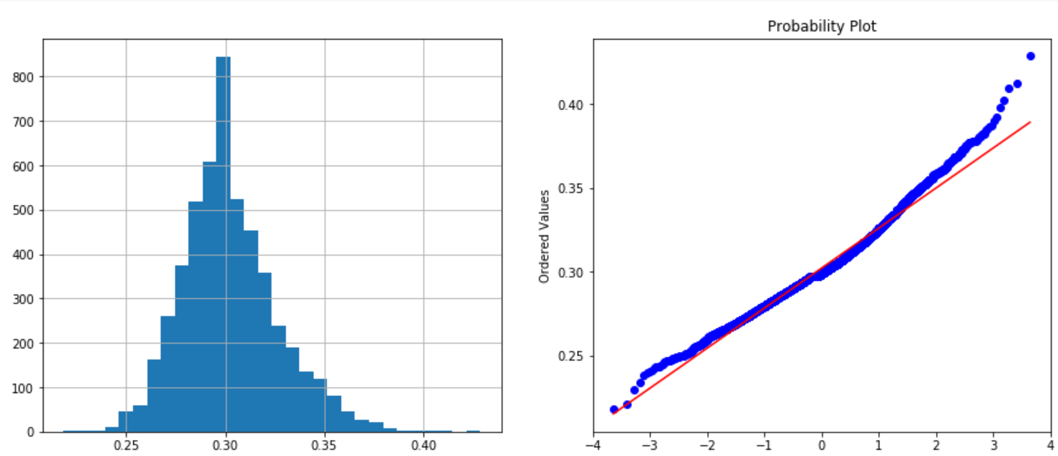
```
[ ] diagnostic_plots(data, 'bmi')
```



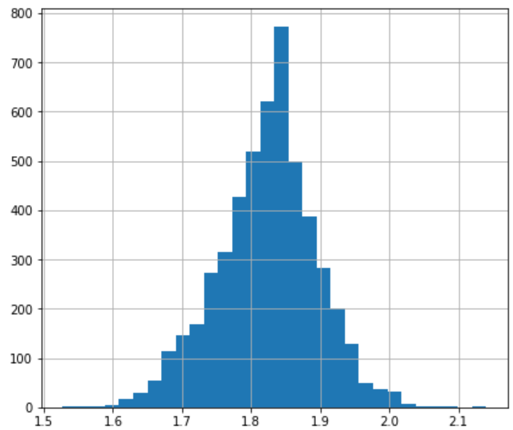

```
[ ] #Логарифмическое преобразование
    data['bmi'] = np.log(data['bmi'])
    diagnostic_plots(data, 'bmi')
```

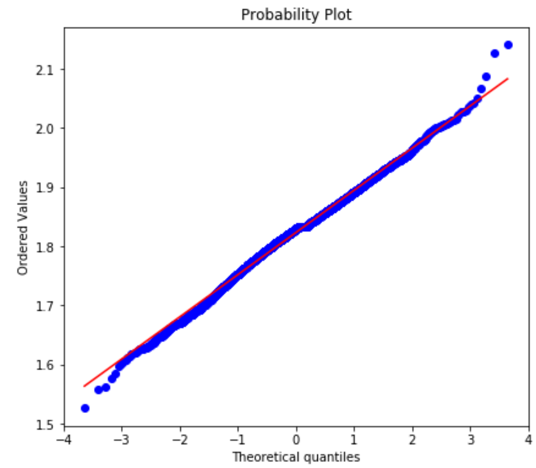



```
[ ] #Обратное преобразование
    data['bmi_reciprocal'] = 1 / (data['bmi'])
    diagnostic_plots(data, 'bmi_reciprocal')
```

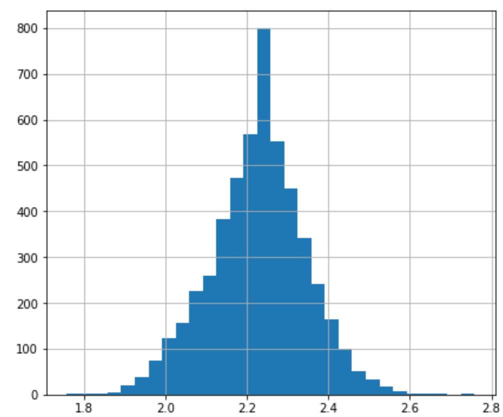


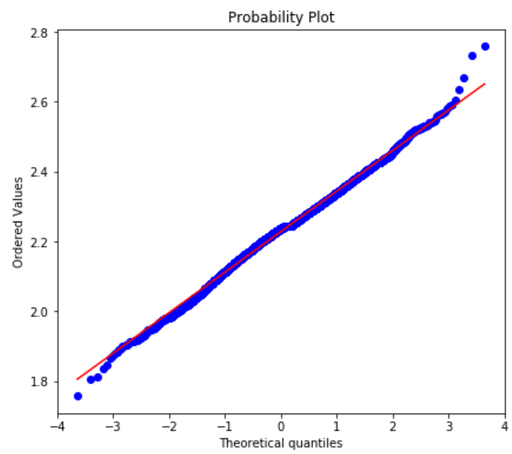
```
[ ]  #Квадратный корень
     data['bmi_sqr'] = data['bmi']**(1/2)
     diagnostic_plots(data, 'bmi_sqr')
```



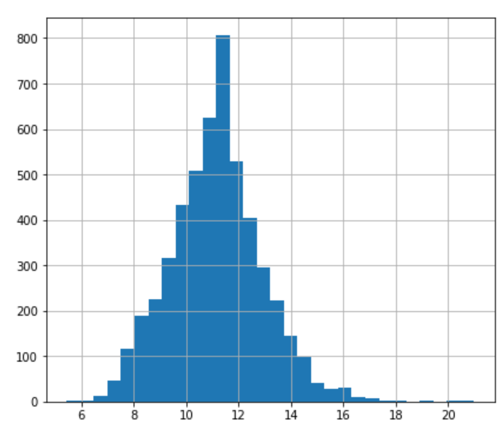


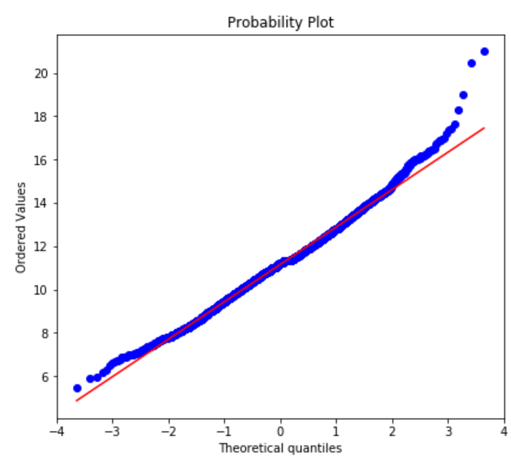

```
[ ]  #Возведение в степень
     data['bmi_exp1'] = data['bmi']**(1/1.5)
     diagnostic_plots(data, 'bmi_exp1')
```



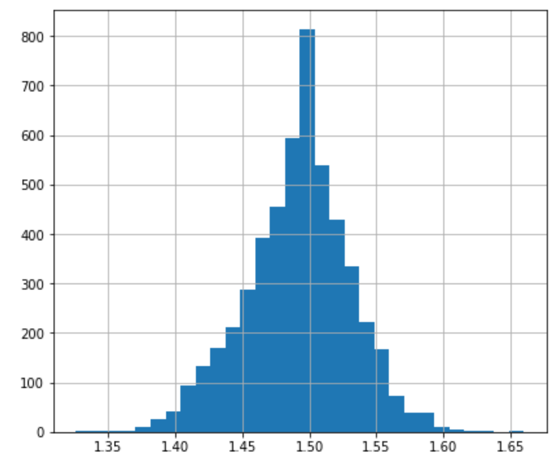


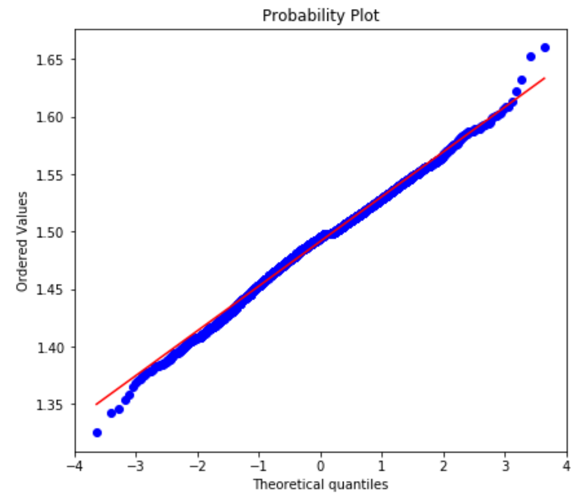

```
[ ]  data['bmi_exp2'] = data['bmi']**(2)
     diagnostic_plots(data, 'bmi_exp2')
```





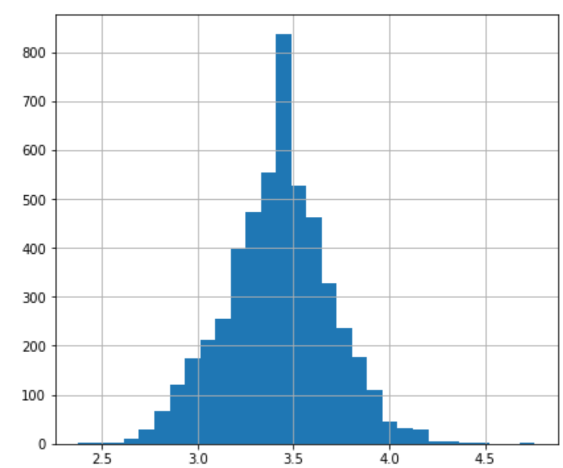
```
[ ] data['bmi_exp3'] = data['bmi']**(0.333)
    diagnostic_plots(data, 'bmi_exp3')
```

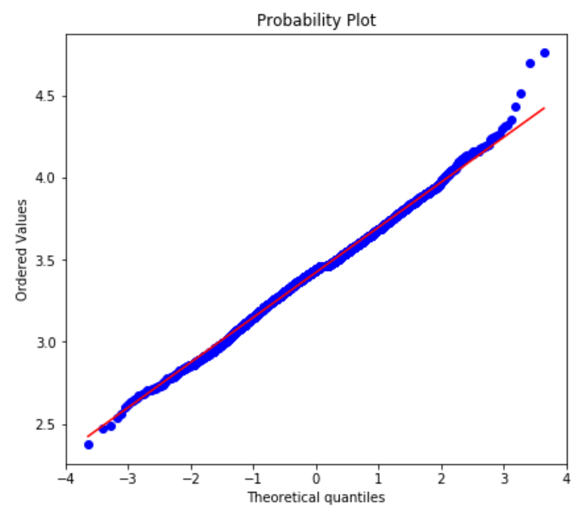





```
[ ] #Преобразования Бокса-Кокса
    data['bmi_boxcox'], param = stats.boxcox(data['bmi'])
    print('Оптимальное значение λ = {}'.format(param))
    diagnostic_plots(data, 'bmi_boxcox')
```

```
Оптимальное значение λ = 0.01648681986277836
```





<u>Вывод:</u>

При выполнении работы выбран датасет для предсказания вероятности проявления у человека сердечного приступа и выполнены следующие задачи: устранение пропусков в данных, кодирование категориальных признаков, нормализация числовых признаков.