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Лабораторная работа №2
«Обработка признаков»

ИСПОЛНИТЕЛЬ:

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

Описание датасета:

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

Ход выполнения:

In [122]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
```

In [123]:
```
data = pd.read_csv('/Users/user/Downloads/stroke.csv')
```

In [124]:
```
data.head()
```

Out[124]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_typ
0	9046	Male	NaN	0	1	Yes	Private	Urba
1	51676	Female	61.0	0	0	Yes	Self-employed	Rura
2	31112	Male	80.0	0	1	Yes	Private	Rura
3	60182	Female	49.0	0	0	Yes	Private	Urba
4	1665	Female	NaN	1	0	Yes	Self-employed	Rura

In [125]:
```
data = data.drop('id', 1)
data.head()
```

Out[125]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_
0	Male	NaN	0	1	Yes	Private	Urban	
1	Female	61.0	0	0	Yes	Self-employed	Rural	
2	Male	80.0	0	1	Yes	Private	Rural	
3	Female	49.0	0	0	Yes	Private	Urban	
4	Female	NaN	1	0	Yes	Self-employed	Rural	

In [126]:
```
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
```

Out[126]:
```
[('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

In [127]:
```
# Доля (процент) пропусков
[(c, data[c].isnull().mean()) for c in data.columns]
```

Out[127]:
```
[('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)]
```

In [128]:
```
# Заполним пропуски
data.dropna(subset=['age'], inplace=True)
```

In [129]:
```
data['gender'] = data['gender'].astype(str).str[0]
```

In [130]:
```
# Заполним пропуски возраста средними значениями
def impute_na(df, variable, value):
    df[variable].fillna(value, inplace=True)
impute_na(data, 'bmi', data['bmi'].mean())
```

In [131]:
```
# Убедимся что нет пустых значений
data.isnull().sum()
```

Out[131]:
```
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
```

In [132]:
```
data.head()
```

Out[132]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_(
1	F	61.0	0	0	Yes	Self-employed	Rural	
2	M	80.0	0	1	Yes	Private	Rural	
3	F	49.0	0	0	Yes	Private	Urban	
5	M	81.0	0	0	Yes	Private	Urban	
6	M	74.0	1	1	Yes	Private	Rural	

Кодирование категориальных признаков

In [133]:
```
from sklearn.preprocessing import LabelEncoder
```

In [134]:
```
le = LabelEncoder()
cat_enc_le = le.fit_transform(data['work_type'])
```

In [135]:
```
data['work_type'].unique()
```

Out[135]:
```
array(['Self-employed', 'Private', 'Govt_job', 'children', 'Never_wo
rked'],
      dtype=object)
```

In [136]:
```
np.unique(cat_enc_le)
```

Out[136]:
```
array([0, 1, 2, 3, 4])
```

In [137]:
```
le.inverse_transform([0, 1, 2, 3,4])
```

Out[137]:
```
array(['Govt_job', 'Never_worked', 'Private', 'Self-employed', 'chil
dren'],
      dtype=object)
```

In [138]:
```
data['smoking_status'].unique()
```

Out[138]:
```
array(['never smoked', 'smokes', 'formerly smoked', 'Unknown'],
      dtype=object)
```

In [139]:
```
#TargetEncoder
from category_encoders.target_encoder import TargetEncoder as ce_Target
```

In [140]:
```
ce_TargetEncoder1 = ce_TargetEncoder()
data_MEAN_ENC = ce_TargetEncoder1.fit_transform(data[data.columns.diffe
```

In [141]:
```
data_MEAN_ENC.head()
```

Out[141]:

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

In [142]:
```
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)
```

In [143]:
```
check_mean_encoding('gender')
```

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

In [144]:
```
check_mean_encoding('smoking_status')
```

```
never smoked - 0.046178343949044585
smokes - 0.05203045685279188
formerly smoked - 0.075
Unknown - 0.029182879377431907
```

In [145]:
```
check_mean_encoding('work_type')
```

```
Self-employed - 0.07607361963190185
Private - 0.04874699622382424
Govt_job - 0.0502283105022831
children - 0.0029112081513828242
Never_worked - 0.0
```

In [146]:
```
#Weight of evidence (WoE) encoding
from category_encoders.woe import WOEEncoder as ce_WOEEncoder
```

In [147]:
```
ce_WOEEncoder1 = ce_WOEEncoder()
data_WOE_ENC = ce_WOEEncoder1.fit_transform(data[data.columns.differenc
```

In [148]:
```
data_WOE_ENC.head()
```

Out[148]:

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

In [149]:
```
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]
            filter_data_zeros = data_filter[data_filter['stroke'] == 0]

            good = filter_data_ones / data_ones
            bad = filter_data_zeros / data_zeros

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

In [150]:
```
check_woe_encoding('gender')
```

```
F - -0.023090517909826913
M - 0.032375673556304815
O - -inf

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: Run
timeWarning: divide by zero encountered in log
  from ipykernel import kernelapp as app
```

In [151]:
```
check_woe_encoding('smoking_status')
```

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

In [152]:
```
check_woe_encoding('work_type')
```

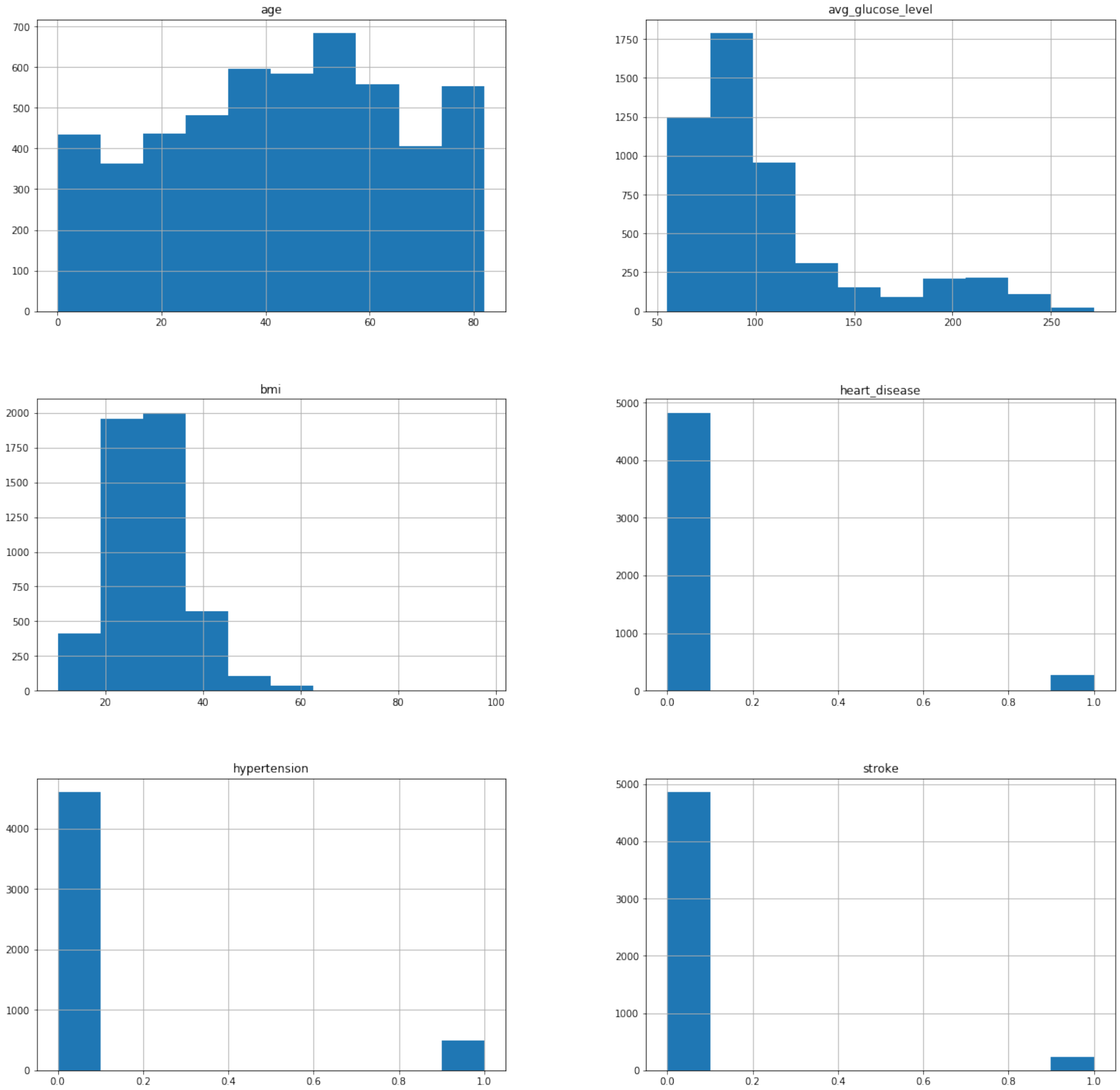
```
Self-employed - 0.5143699860391127
Private - 0.040164341532197056
Govt_job - 0.07165802189096712
children - -2.8249708289083655
Never_worked - -inf

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: Run
timeWarning: divide by zero encountered in log
  from ipykernel import kernelapp as app
```

Нормализация числовых признаков

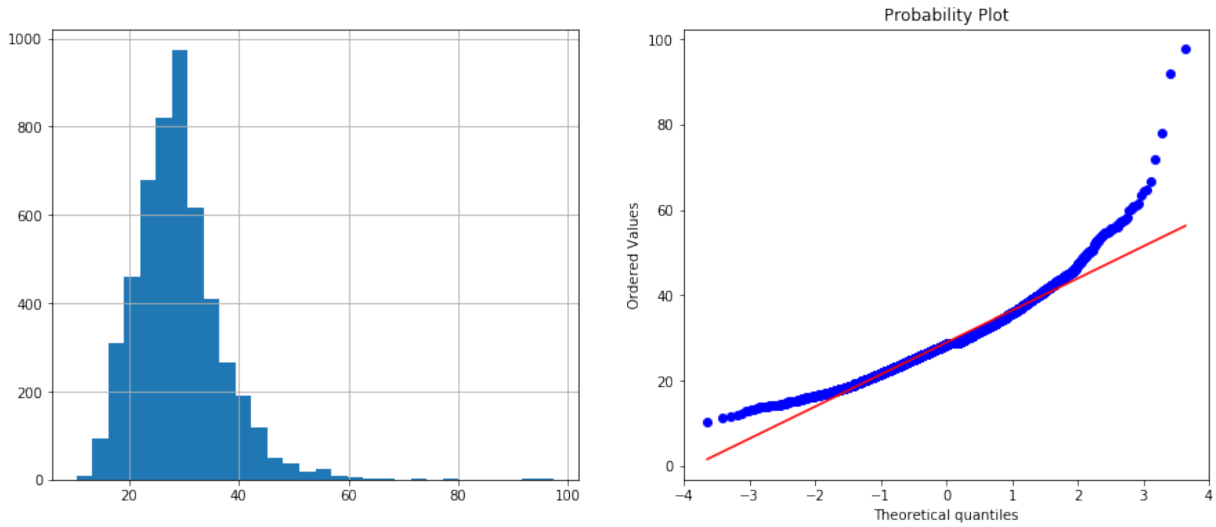
In [153]:
```
def diagnostic_plots(df, variable):
    plt.figure(figsize=(15,6))
    # гистограмма
    plt.subplot(1, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(1, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    plt.show()
```

In [154]:

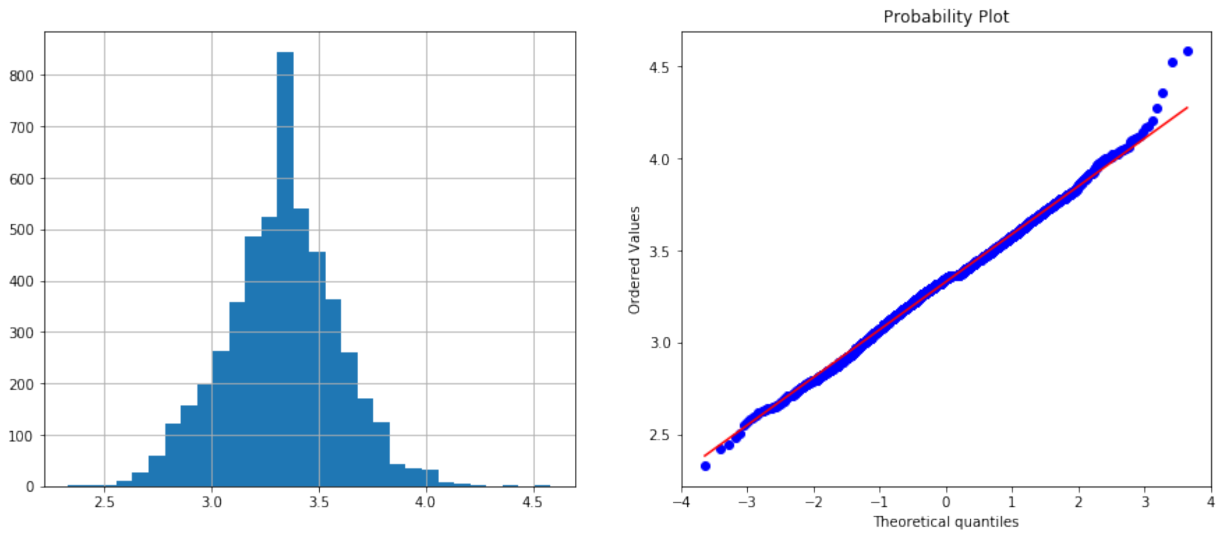
```
data.hist(figsize=(20,20))
plt.show()
```



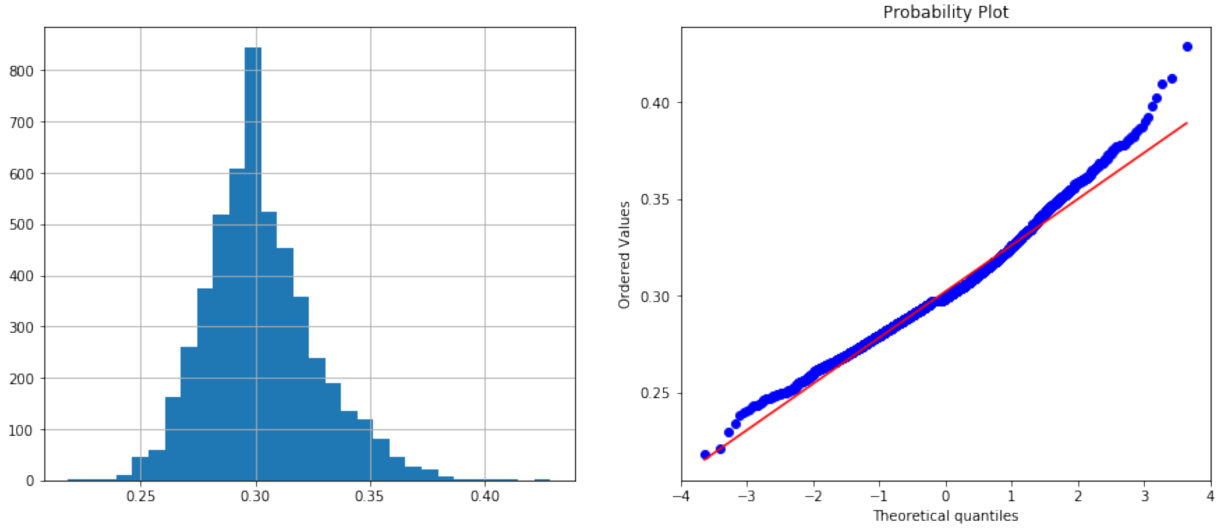
In [170]:
```
diagnostic_plots(data, 'bmi')
```



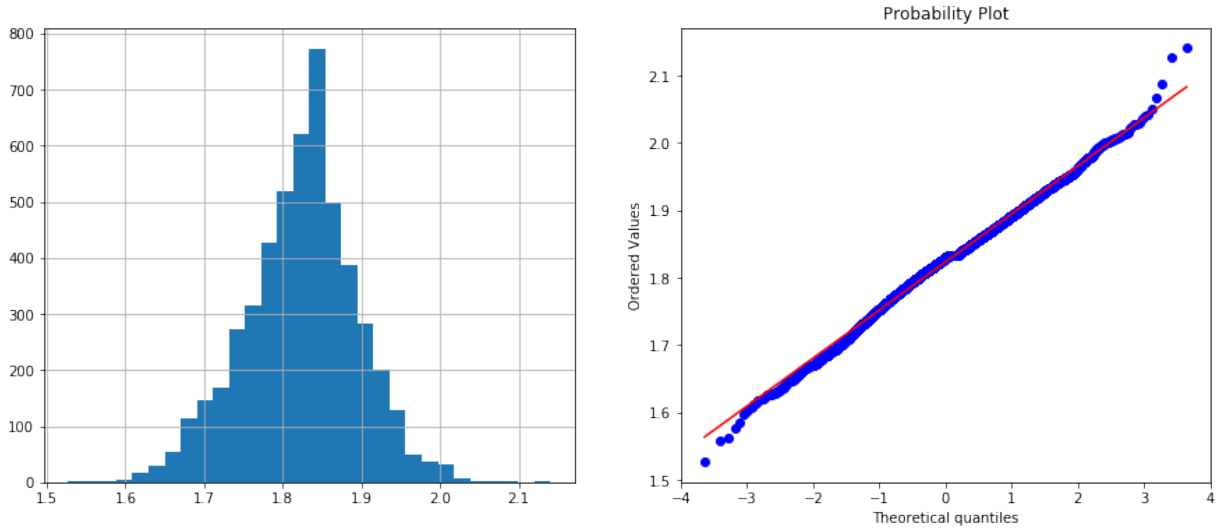
In [171]:
```
#Логарифмическое преобразование
data['bmi'] = np.log(data['bmi'])
diagnostic_plots(data, 'bmi')
```



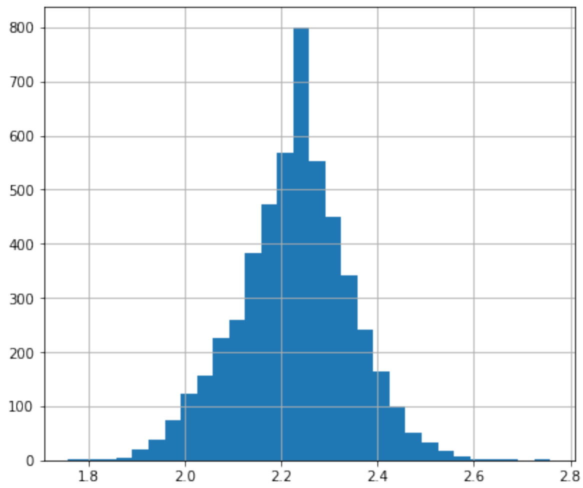
In [172]:
```
#Обратное преобразование
data['bmi_reciprocal'] = 1 / (data['bmi'])
diagnostic_plots(data, 'bmi_reciprocal')
```

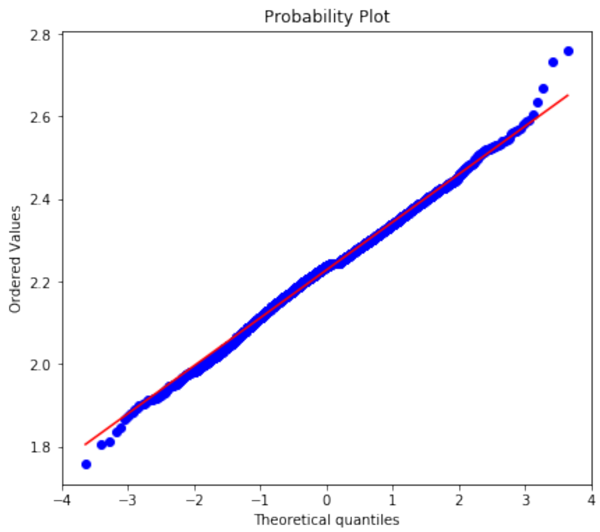


In [173]:
```
#Квадратный корень
data['bmi_sqr'] = data['bmi']**(1/2)
diagnostic_plots(data, 'bmi_sqr')
```

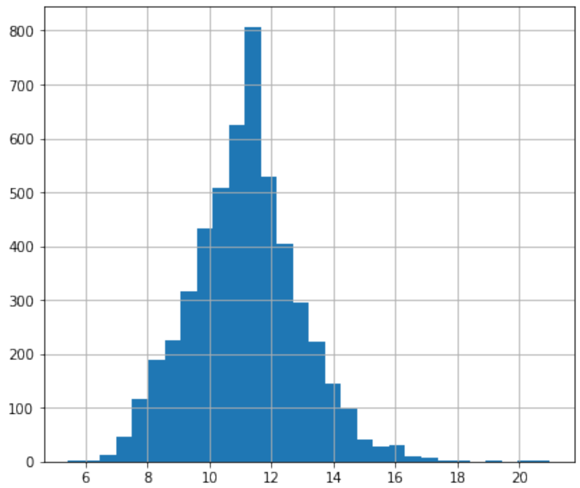


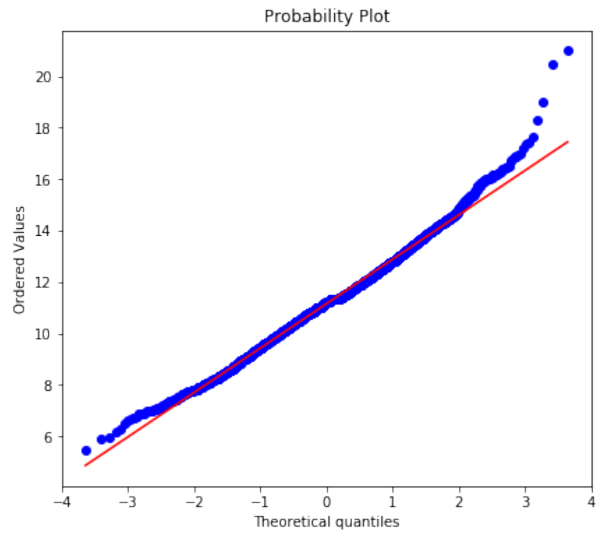
In [174]:
```
#Возведение в степень
data['bmi_exp1'] = data['bmi']**(1/1.5)
diagnostic_plots(data, 'bmi_exp1')
```



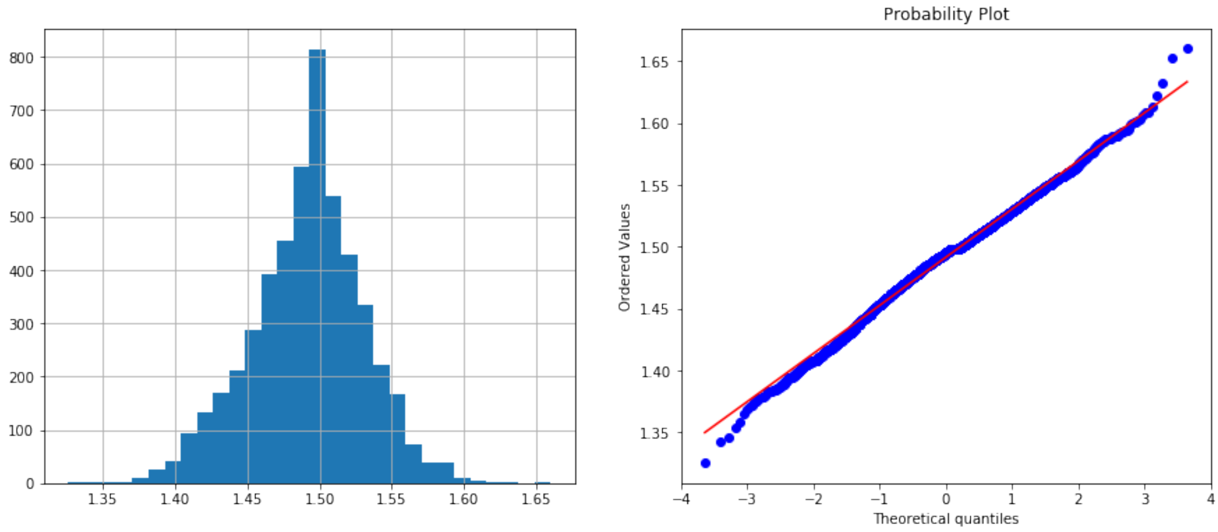


In [175]:
```
data['bmi_exp2'] = data['bmi']**(2)
diagnostic_plots(data, 'bmi_exp2')
```



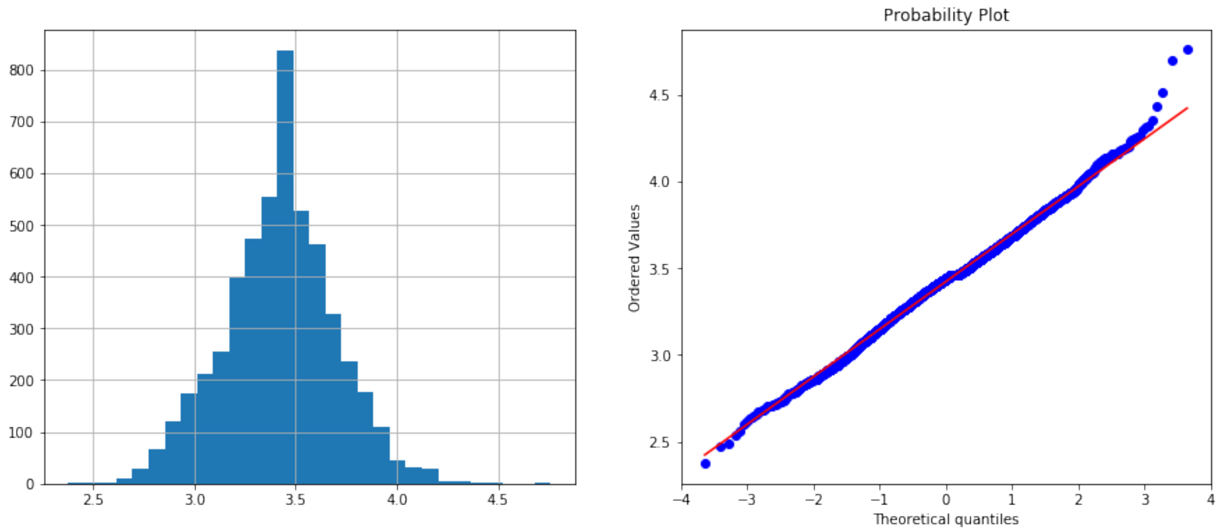


In [176]:
```
data['bmi_exp3'] = data['bmi']**(0.333)
diagnostic_plots(data, 'bmi_exp3')
```



In [169]:
```
#Преобразованиея Бокса-Кокса
data['bmi_boxcox'], param = stats.boxcox(data['bmi'])
print('Оптимальное значение λ = {}'.format(param))
diagnostic_plots(data, 'bmi_boxcox')
```

```
Оптимальное значение λ = 0.016486819862778361
```



In [ ]: