Московский государственный технический университет им. Н.Э. Баумана
Кафедра «Системы обработки информации и управления»

Лабораторная работа №2
по дисциплине
«Методы машинного обучения»
на тему

«Обработка признаков (часть 1)»

Выполнил:
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1. Цель лабораторной работы

Изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

2. 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. нормализация числовых признаков.

устранение пропусков в данных

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from IPython.display import Image
%matplotlib inline
sns.set(style="ticks")
```

```
[ ] #Загрузка и первичный анализ данных#
```

```
[ ] # Будем использовать только обучающую выборку
data = pd.read_csv('Movies.csv')
```

```
[ ] data.shape
```

```
(866, 13)
```

```
[ ] data.isnull().sum()
```

```
index            0
Title            0
Release Date    13
Year            12
Description    866
URL              0
Rating          19
Runtime         19
Genres           0
Votes           19
Directors        8
Series           0
Order            0
dtype: int64
```

```
[ ] #data type#
list(zip(data.columns, [i for i in data.dtypes]))
```

```
[('index', dtype('int64')),
 ('Title', dtype('O')),
 ('Release Date', dtype('O')),
 ('Year', dtype('float64')),
 ('Description', dtype('float64')),
 ('URL', dtype('O')),
 ('Rating', dtype('float64')),
 ('Runtime', dtype('float64')),
 ('Genres', dtype('O')),
 ('Votes', dtype('float64')),
 ('Directors', dtype('O')),
 ('Series', dtype('O')),
 ('Order', dtype('int64'))]
```

```python
# Колонки с пропусками
hcols_with_na = [c for c in data.columns if data[c].isnull().sum() > 0]
hcols_with_na
```

```
['Release Date',
 'Year',
 'Description',
 'Rating',
 'Runtime',
 'Votes',
 'Directors']
```

```python
data.shape
```

```
(866, 13)
```

```python
# Количество пропусков
[(c, data[c].isnull().sum()) for c in hcols_with_na]
```

```
[('Release Date', 13),
 ('Year', 12),
 ('Description', 866),
 ('Rating', 19),
 ('Runtime', 19),
 ('Votes', 19),
 ('Directors', 8)]
```

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

```
[('Release Date', 0.015011547344110854),
 ('Year', 0.013856812933025405),
 ('Description', 1.0),
 ('Rating', 0.021939953810623556),
 ('Runtime', 0.021939953810623556),
 ('Votes', 0.021939953810623556),
 ('Directors', 0.009237875288683603)]
```

```python
# Колонки для которых удаляются пропуски
hcols_with_na_temp = ['Directors', 'Year', 'Votes']
```

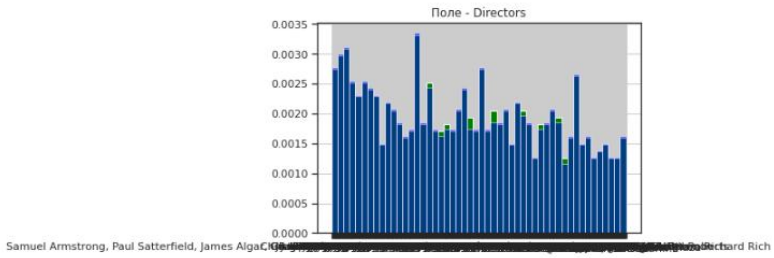
```python
res = data.dropna(axis=1, how='any')
```

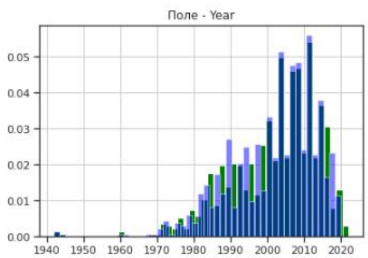
```python
# Удаление пропусков
data_drop = data[hcols_with_na_temp].dropna()
data_drop.shape
```

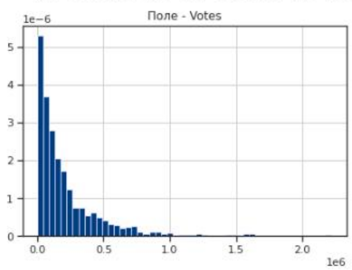
```
(847, 3)
```

```python
def plot_hist_diff(old_ds, new_ds, cols):
    """
    Разница между распределениями до и после устранения пропусков
    """
    for c in cols:
        fig = plt.figure()
        ax = fig.add_subplot(111)
        ax.title.set_text('Поле - ' + str(c))
        old_ds[c].hist(bins=50, ax=ax, density=True, color='green')
        new_ds[c].hist(bins=50, ax=ax, color='blue', density=True, alpha=0.5)
        plt.show()
```

```python
plot_hist_diff(data, data_drop, hcols_with_na_temp)
```







кодирование категориальных признаков

```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

[4]
```python
# Будем использовать только обучающую выборку
data = pd.read_csv('flight.csv')
```

```python
# размер набора данных
data.shape
```

```
(851, 14)
```

[6]
```python
data.head()
```

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Food and drink	Seat comfort	Baggage handling	Departure Delay	Arrival Delay	satisfaction
0	0	19556	Female	Loyal Customer	52	Business travel	Eco	160	3	3	5	50	44.0	satisfied
1	1	90035	Female	Loyal Customer	36	Business travel	Business	2863	5	5	4	0	0.0	satisfied
2	2	12360	Male	disloyal Customer	20	Business travel	Eco	192	2	2	3	0	0.0	neutral or dissatisfied
3	3	77959	Male	Loyal Customer	44	Business travel	Business	3377	3	4	1	0	6.0	satisfied
4	4	36875	Female	Loyal Customer	49	Business travel	Eco	1182	4	2	2	0	20.0	satisfied

[7]
```python
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
```

```
[('Unnamed: 0', ('int64', 0)),
 ('id', ('int64', 0)),
 ('Gender', ('object', 0)),
 ('Customer Type', ('object', 0)),
 ('Age', ('int64', 0)),
 ('Type of Travel', ('object', 0)),
 ('Class', ('object', 0)),
 ('Flight Distance', ('int64', 0)),
 ('Food and drink', ('int64', 0)),
 ('Seat comfort', ('int64', 0)),
 ('Baggage handling', ('int64', 0)),
 ('Departure Delay', ('int64', 0)),
 ('Arrival Delay', ('float64', 2)),
 ('satisfaction', ('object', 0))]
```

```python
# Используем некоторые признаки
cols_filter = ['id', 'Gender', 'Age', 'Class', 'Flight Distance',
               'Seat comfort', 'Arrival Delay', 'satisfaction']
data = data[cols_filter]
data.head()
```

	id	Gender	Age	Class	Flight Distance	Seat comfort	Arrival Delay	satisfaction
0	19556	Female	52	Eco	160	3	44.0	satisfied
1	90035	Female	36	Business	2863	5	0.0	satisfied
2	12360	Male	20	Eco	192	2	0.0	neutral or dissatisfied
3	77959	Male	44	Business	3377	4	6.0	satisfied
4	36875	Female	49	Eco	1182	2	20.0	satisfied

[9]
```python
# Заполним пропуски
data.dropna(subset=['Flight Distance', 'Arrival Delay'], inplace=True)
```

[10]
```python
# От каюты оставляет только первую букву
# и убираем каюты типа T так как их мало
data['Arrival Delay'] = data['Arrival Delay'].astype(str).str[0]
data = data[data['Arrival Delay'] != '0']
```

[11]
```python
# Убедимся что нет пустых значений
data.isnull().sum()
```

```
id                 0
Gender             0
Age                0
Class              0
Flight Distance    0
Seat comfort       0
Arrival Delay      0
satisfaction       0
dtype: int64
```

LABEl ENCODING

双击（或按回车键）即可修改

```
[ ] from sklearn.preprocessing import LabelEncoder
    le = LabelEncoder()
    cat_enc_le = le.fit_transform(data['Gender'])
    data['Gender'].unique()
```

```
array(['Female', 'Male'], dtype=object)
```

```
[ ] np.unique(cat_enc_le)
```

```
array([0, 1])
```

```
le.inverse_transform([0, 1])
```

```
array(['Female', 'Male'], dtype=object)
```

```
[ ] data['Gender']=le.fit_transform(data['Gender'])
```

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

	id	Gender	Age	Class	Flight Distance	Seat comfort	Arrival Delay	satisfaction
0	19556	0	52	Eco	160	3	4	satisfied
3	77959	1	44	Business	3377	4	6	satisfied
4	36875	0	49	Eco	1182	2	2	satisfied
7	97286	0	43	Business	2556	5	6	satisfied
9	62482	0	46	Business	1744	4	1	satisfied

ONE HOT CODING

```
[12] from sklearn.preprocessing import OneHotEncoder
     ohe = OneHotEncoder()
     cat_enc_ohe = ohe.fit_transform(data[['Class']])
     cat_enc_ohe
```

```
<365x3 sparse matrix of type '<class 'numpy.float64'>'
        with 365 stored elements in Compressed Sparse Row format>
```

```
[13] cat_enc_ohe.todense()[0:10]
```

```
matrix([[0., 1., 0.],
        [1., 0., 0.],
        [0., 1., 0.],
        [1., 0., 0.],
        [1., 0., 0.],
        [0., 1., 0.],
        [1., 0., 0.],
        [1., 0., 0.],
        [0., 1., 0.],
        [1., 0., 0.]])
```

```
pd.get_dummies(data[['Class']]).head()
```

	Class_Business	Class_Eco	Class_Eco Plus
0	0	1	0
3	1	0	0
4	0	1	0
7	1	0	0
9	1	0	0

```
[15] # добавление отдельной колонки, признака пустых значений
     pd.get_dummies(data[['Class']], dummy_na=True).head()
```

	Class_Business	Class_Eco	Class_Eco Plus	Class_nan
0	0	1	0	0
3	1	0	0	0
4	0	1	0	0
7	1	0	0	0
9	1	0	0	0

```
[16] pip install category_encoders
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting category_encoders
  Downloading category_encoders-2.6.0-py2.py3-none-any.whl (81 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 81.2/81.2 KB 3.3 MB/s eta 0:00:00
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.10.1)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.4.4)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.2.2)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (0.5.3)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (0.13.5)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.22.4)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-packages (from pandas>=1.0.5->category_encoders) (2022.7.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.9/dist-packages (from pandas>=1.0.5->category_encoders) (2.8.2)
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist-packages (from scikit-learn>=0.20.0->category_encoders) (3.1.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-packages (from scikit-learn>=0.20.0->category_encoders) (1.1.1)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.9/dist-packages (from statsmodels>=0.9.0->category_encoders) (23.0)
Installing collected packages: category_encoders
Successfully installed category_encoders-2.6.0
```

```
from category_encoders.one_hot import OneHotEncoder as ce_OneHotEncoder
ce_OneHotEncoder1 = ce_OneHotEncoder()
data_OHE = ce_OneHotEncoder1.fit_transform(data[data.columns.difference(['Gender'])])
data_OHE
```

	Age	Arrival Delay_1	Arrival Delay_2	Arrival Delay_3	Arrival Delay_4	Arrival Delay_5	Arrival Delay_6	Arrival Delay_7	Arrival Delay_8	Arrival Delay_9	Class_1	Class_2	Class_3	Flight Distance	Seat comfort	id	satisfaction_1	satisfaction_2
0	52	1	0	0	0	0	0	0	0	0	1	0	0	160	3	19556	1	0
3	44	0	1	0	0	0	0	0	0	0	0	1	0	3377	4	77959	1	0
4	49	0	0	1	0	0	0	0	0	0	1	0	0	1182	2	36875	1	0
7	43	0	1	0	0	0	0	0	0	0	0	1	0	2556	5	97286	1	0
9	46	0	0	0	1	0	0	0	0	0	0	1	0	1744	4	62482	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
839	53	0	0	1	0	0	0	0	0	0	0	1	0	3648	2	122646	0	1
843	35	0	0	0	1	0	0	0	0	0	1	0	0	689	1	103577	0	1
845	65	0	0	0	1	0	0	0	0	0	1	0	0	2342	2	129555	0	1
848	37	0	0	0	0	0	0	0	1	0	1	0	0	173	3	19580	0	1
850	49	1	0	0	0	0	0	0	0	0	1	0	0	748	5	42198	1	0

365 rows × 18 columns

Count (frequency) encoding

```
[ ] from category_encoders.count import CountEncoder as ce_CountEncoder
    ce_CountEncoder1 = ce_CountEncoder()
    data_COUNT_ENC = ce_CountEncoder1.fit_transform(data[data.columns.difference(['Gender'])])
    data_COUNT_ENC
```

	Age	Arrival Delay	Class	Flight Distance	Seat comfort	id	satisfaction
0	52	49	167	160	3	19556	153
3	44	25	170	3377	4	77959	153
4	49	60	167	1182	2	36875	153
7	43	25	170	2556	5	97286	153
9	46	117	170	1744	4	62482	153
...	...	...	...	...	...	...	...
839	53	60	170	3648	2	122646	212
843	35	117	167	689	1	103577	212
845	65	117	167	2342	2	129555	212
848	37	16	167	173	3	19580	212
850	49	49	167	748	5	42198	153

365 rows × 7 columns

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

```
array(['Eco', 'Business', 'Eco Plus'], dtype=object)
```

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

```
array([167, 170,  28])
```

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

	Age	Arrival Delay	Class	Flight Distance	Seat comfort	id	satisfaction
0	52	0.134247	0.457534	160	3	19556	0.419178
3	44	0.068493	0.465753	3377	4	77959	0.419178
4	49	0.164384	0.457534	1182	2	36875	0.419178
7	43	0.068493	0.465753	2556	5	97286	0.419178
9	46	0.320548	0.465753	1744	4	62482	0.419178
...	...	...	...	...	...	...	...
839	53	0.164384	0.465753	3648	2	122646	0.580822
843	35	0.320548	0.457534	689	1	103577	0.580822
845	65	0.320548	0.457534	2342	2	129555	0.580822
848	37	0.043836	0.457534	173	3	19580	0.580822

Helmert encoding

```
[ ] from category_encoders.helmert import HelmertEncoder as ce_HelmertEncoder
    ce_HelmertEncoder1 = ce_HelmertEncoder()
    data_HELM_ENC = ce_HelmertEncoder1.fit_transform(data[data.columns.difference(['Gender'])], data['Gender'])
    data_HELM_ENC
```

```
/usr/local/lib/python3.8/dist-packages/category_encoders/base_contrast_encoder.py:126: FutureWarning: Intercept column might not be added anymore in future releases (c.f. issue #370)
  warnings.warn("Intercept column might not be added anymore in future releases (c.f. issue #370)",
```

	intercept	Age	Arrival Delay_0	Arrival Delay_1	Arrival Delay_2	Arrival Delay_3	Arrival Delay_4	Arrival Delay_5	Arrival Delay_6	Arrival Delay_7	Class_0	Class_1	Flight Distance	Seat comfort	id	satisfaction_0
0	1	52	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	160	3	19556	-1.0
3	1	44	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	3377	4	77959	-1.0
4	1	49	0.0	2.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1182	2	36875	-1.0
7	1	43	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	2556	5	97286	-1.0
9	1	46	0.0	0.0	3.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	1744	4	62482	-1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
839	1	53	0.0	2.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	3648	2	122646	1.0
843	1	35	0.0	0.0	3.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	689	1	103577	1.0
845	1	65	0.0	0.0	3.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	2342	2	129555	1.0
848	1	37	0.0	0.0	0.0	0.0	0.0	0.0	7.0	-1.0	-1.0	-1.0	173	3	19580	1.0
850	1	49	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	748	5	42198	-1.0

365 rows × 16 columns

```python
class MetricLogger:

    def __init__(self):
        self.df = pd.DataFrame(
            {'metric': pd.Series([], dtype='str'),
            'alg': pd.Series([], dtype='str'),
            'value': pd.Series([], dtype='float')})

    def add(self, metric, alg, value):
        """
        Добавление значения
        """
        # Удаление значения если оно уже было ранее добавлено
        self.df.drop(self.df[(self.df['metric']==metric)&(self.df['alg']==alg)].index, inplace = True)
        # Добавление нового значения
        temp = [{'metric':metric, 'alg':alg, 'value':value}]
        self.df = self.df.append(temp, ignore_index=True)

    def get_data_for_metric(self, metric, ascending=True):
        """
        Формирование данных с фильтром по метрике
        """
        temp_data = self.df[self.df['metric']==metric]
        temp_data_2 = temp_data.sort_values(by='value', ascending=ascending)
        return temp_data_2['alg'].values, temp_data_2['value'].values

    def plot(self, str_header, metric, ascending=True, figsize=(5, 5)):
        """
        Вывод графика
        """
        array_labels, array_metric = self.get_data_for_metric(metric, ascending)
        fig, ax1 = plt.subplots(figsize=figsize)
        pos = np.arange(len(array_metric))
        rects = ax1.barh(pos, array_metric,
                         align='center',
                         height=0.5,
                         tick_label=array_labels)
        ax1.set_title(str_header)
        for a,b in zip(pos, array_metric):
            plt.text(0.5, a-0.05, str(round(b,3)), color='white')
        plt.show()
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
```

```
[ ] clas_models_dict = {'LogR': LogisticRegression(max_iter=1000),
                        'KNN_5':KNeighborsClassifier(n_neighbors=5),
                        'Tree':DecisionTreeClassifier(),
                        'GB': GradientBoostingClassifier(),
                        'RF':RandomForestClassifier(n_estimators=50, random_state=1, max_depth=3)}
```

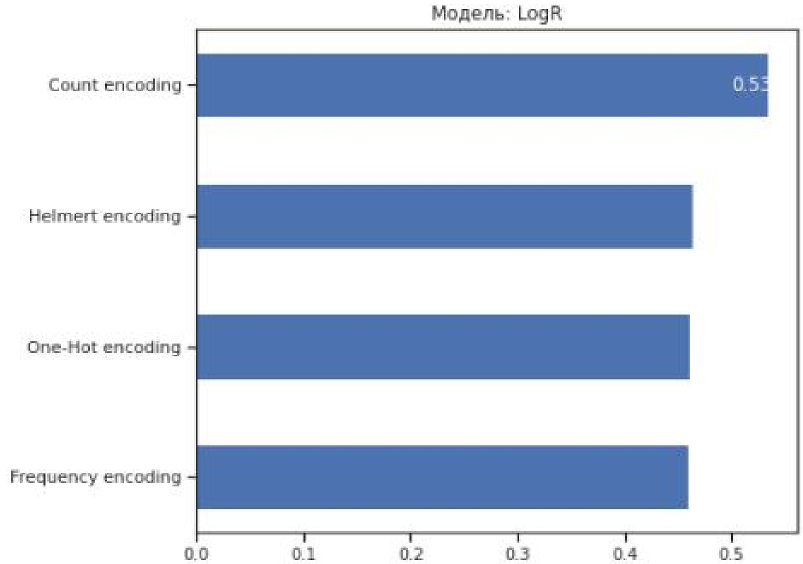
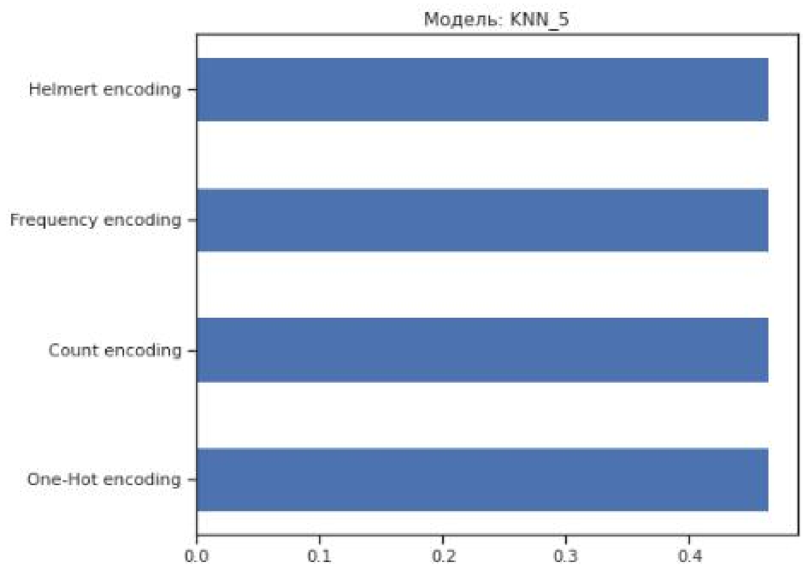
```
[ ] X_data_dict = {'One-Hot encoding': data_OHE,
                   'Count encoding': data_COUNT_ENC,
                   'Frequency encoding': data_FREQ_ENC,
                   'Helmert encoding': data_HELM_ENC}
```

```
def test_models(clas_models_dict, X_data_dict, y_data):

    logger = MetricLogger()

    for model_name, model in clas_models_dict.items():

        for data_name, X_data in X_data_dict.items():

            X_train, X_test, y_train, y_test = train_test_split(
                X_data, y_data, test_size=0.3, random_state=1)

            model.fit(X_train, y_train)
            pred1 = model.predict_proba(X_train)
            pred2 = model.predict_proba(X_test)
            roc_auc = roc_auc_score(y_test, pred2[:, 1])
            logger.add(model_name, data_name, roc_auc)

    return logger
```

```
[ ] %%time
logger = test_models(clas_models_dict, X_data_dict, data['Gender'])
```

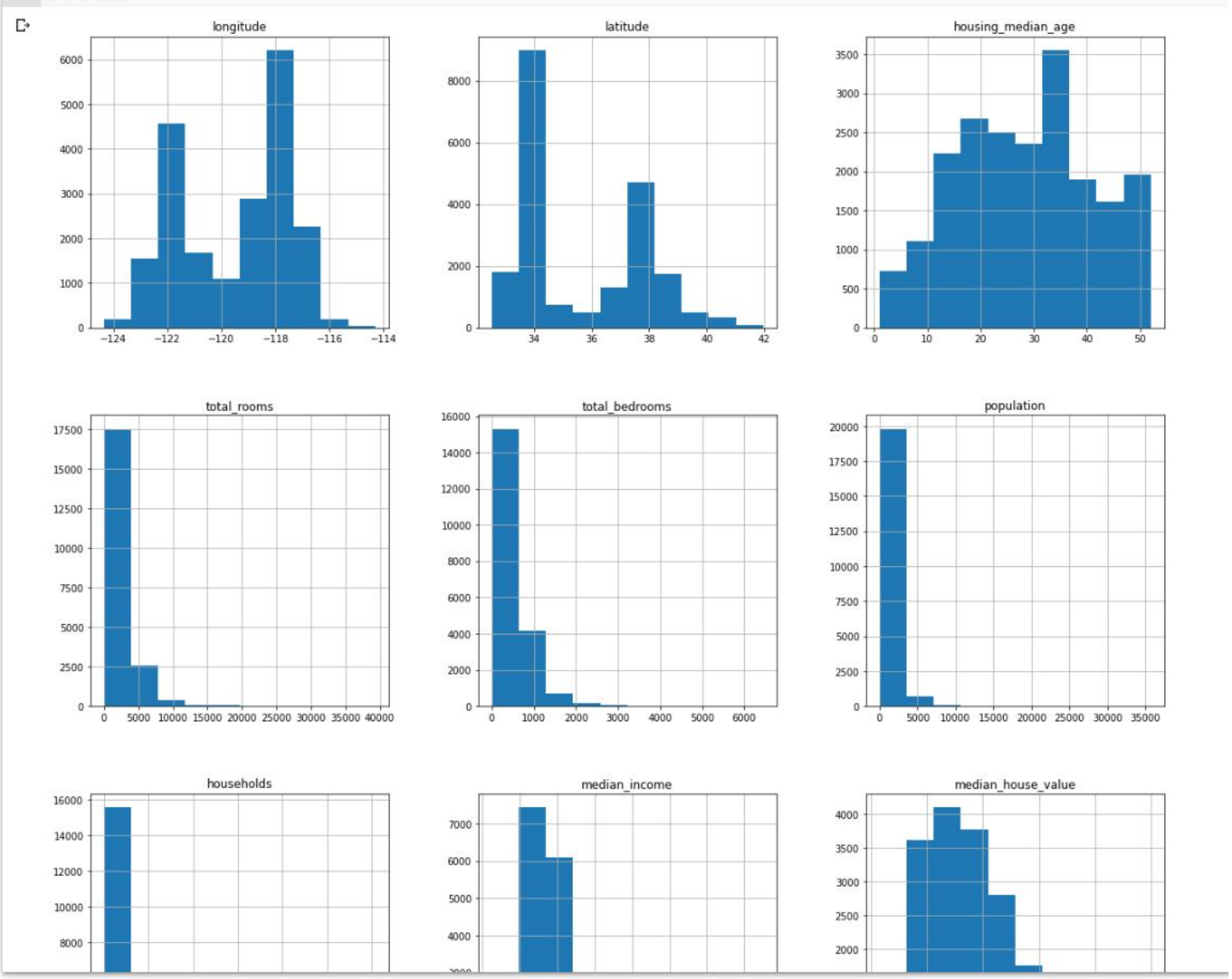
```
CPU times: user 1.4 s, sys: 156 ms, total: 1.55 s
Wall time: 1.58 s
```

```
[ ] # Построим графики метрик качества модели
for model in clas_models_dict:
    logger.plot('Модель: ' + model, model, figsize=(7, 6))
```


Модель: LogR
Count encoding
Helmert encoding
One-Hot encoding
Frequency encoding
0.53
0.0
0.1
0.2
0.3
0.4
0.5

Модель: KNN_5
Helmert encoding
Frequency encoding
Count encoding
One-Hot encoding
0.0
0.1
0.2
0.3
0.4

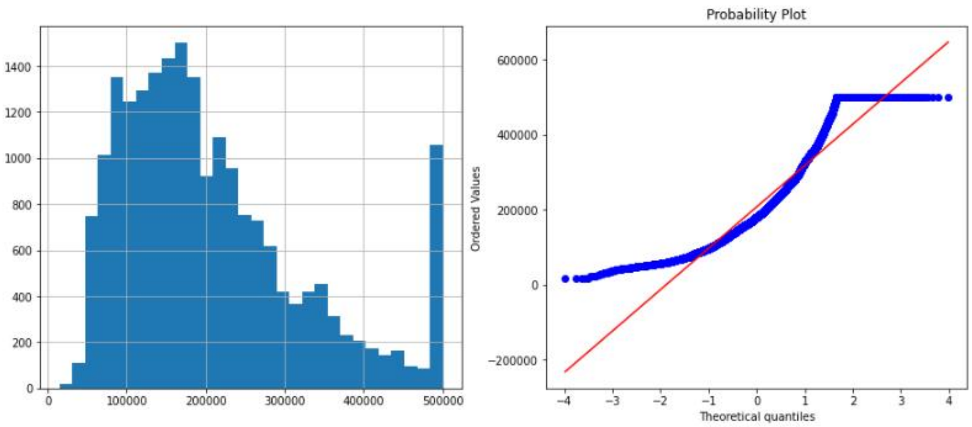
нормализация числовых признаков

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
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()
# Будем использовать только обучающую выборку
data = pd.read_csv('housing.csv')
data.hist(figsize=(20,20))
plt.show()
```



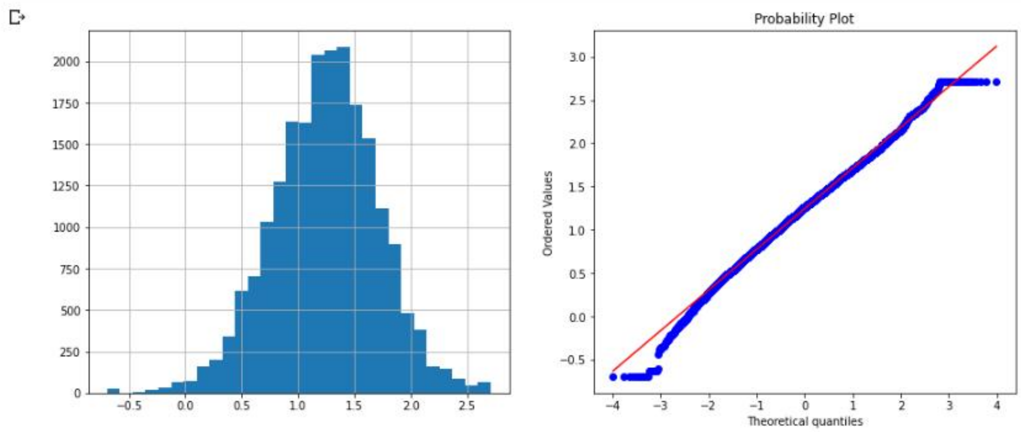
Исходное распределение

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



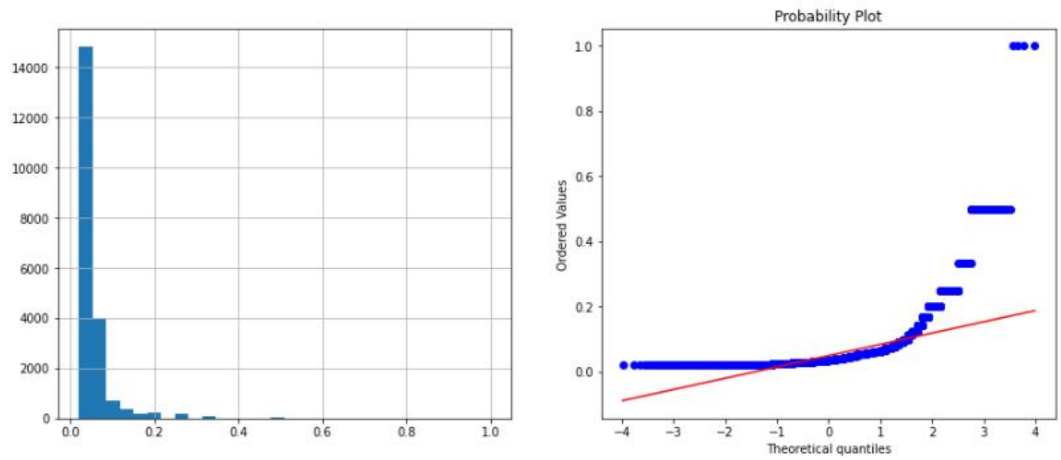
Логарифмическое преобразование

```
data['median_income'] = np.log(data['median_income'])
diagnostic_plots(data, 'median_income')
```



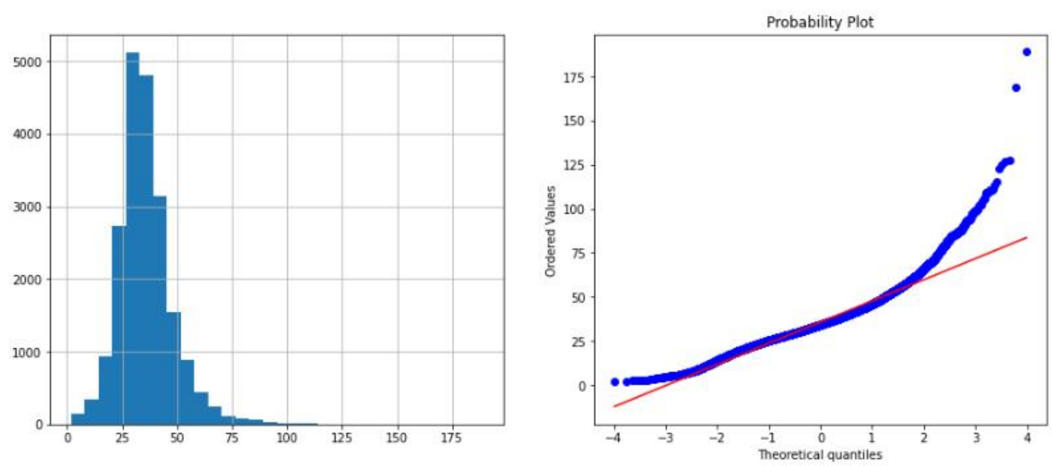
Обратное преобразование

```
[ ] data['median_house_value'] = 1 / (data['housing_median_age'])
    diagnostic_plots(data, 'median_house_value')
```



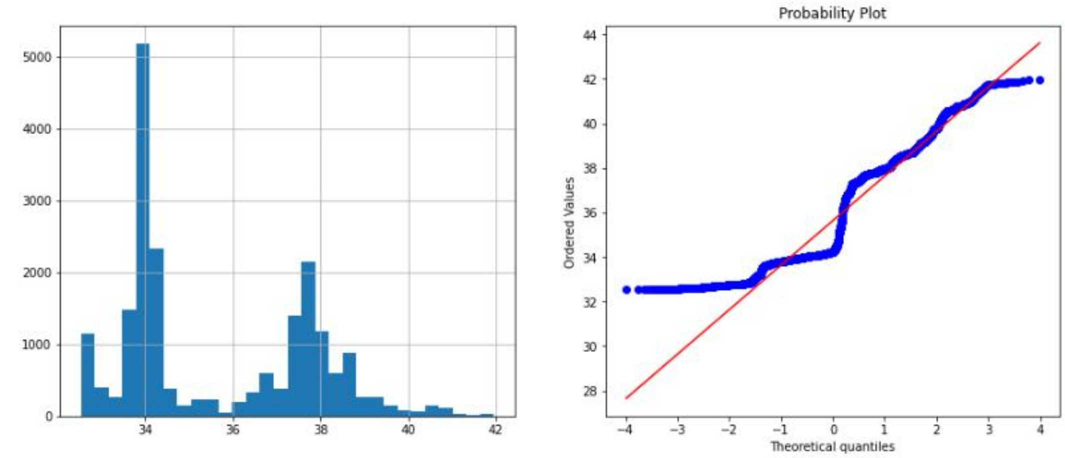
Квадратный корень

```
data['households'] = data['population']**(1/2)
diagnostic_plots(data, 'households')
```



Возведение в степень

```
data['latitude_exp2'] = data['latitude']**(2)
diagnostic_plots(data, 'latitude')
```




```
data['Value_boxcox'], param = stats.boxcox(data['median_house_value'])
print('Оптимальное значение λ = {}'.format(param))
diagnostic_plots(data, 'Value_boxcox')
```

```
Оптимальное значение λ = -0.8093981353591877
```