Рубежный контроль №1 ИУ5-24М

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Вариант 3

Для студентов группы ИУ5-24М - для произвольной колонки данных построить график "Скрипичная диаграмма (violin plot)".

Задача №3.

Для набора данных проведите кодирование одного (произвольного) категориального признака с использованием метода "weight of evidence (WoE) encoding".

Задача №23.

Для набора данных для одного (произвольного) числового признака проведите обнаружение и удаление выбросов на основе правила трех сигм.

[6]

5 сек.

pip install category_encoders

Looking in indexes: 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)

KB 4.7 MB/s eta 0:00:00

Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.4.4)

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: scipy>=1.0.0 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (1.10.1)

Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.9/dist-packages (from category_encoders) (0.5.3)

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: 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: 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: 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: packaging>=21.3 in /usr/local/lib/python3.9/dist-packages (from statsmodels>=0.9.0->category_encoders) (23.0)

 $In stalling\ collected\ packages:\ category_encoders$

Successfully installed category_encoders-2.6.0

[123]

0 сек.

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

from category_encoders.woe import WOEEncoder as ce_WOEEncoder

[124]

2 сек.

from google.colab import drive

drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

Загрузка набора данных

[125]

0 сек.

```
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/MMO/sport.csv', sep=",")
# Первые 5 строк датасета
data = data.drop(['ID'], axis=1)
data.head()
```



Кодирование категориального признака

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

```
City
                      Event
                                       Medal
                                                 NOC
                                                                Season
                                                                         Sport
                                                                                   Teal Year
      Age
           0.884288
                   0.373462
                            0.884288 0.153897 -0.725150
                                                      0.000000 0.020748 -0.319685 -0.725150
   0
                   -0.725150
                           -1.371777 0.153897 -0.725150
                                                      0.000000 0.020748 -0.032003 -0.725150 2012
          -0.106111
      24.0
           0.255679
                    1.066610
                            0.255679 0.153897 -0.725150
                                                      0.000000 0.020748
                                                                       0.373462
                                                                                0.000000 1920
      34.0 -1.130615
                   0.000000
                           -1.823762 0.022064
                                            -0.725150
                                                      0.000000 0.020748
                                                                       0.000000
                                                                                0.000000
                                                                                        1900
      31.0 -0.175104
                   0.000000
                           -0.175104 0.153897
                                             0.335722
                                                      0.000000 0.020748
                                                                       0.000000
                                                                                0.335722 2000
      19.0
          -0.319685
                   -0.437468
                            -0.319685
                                    0.153897
                                            -1.130615 -0.725150 0.020748 -0.186153
                                                                                       1988
  286
                            287
      23.0
           0.884288
                  -0.437468
     22.0 -1.743719 -2.922374 -1.743719 0.153897 -1.130615 -2.922374 0.020748 -0.619789 -1.130615 2008
          -0.106111 -2.922374 -1.371777 0.153897 -1.130615 -2.922374 0.020748 -0.619789 -1.130615 2012
  290 25.0 0.884288 -0.437468 0.884288 0.153897 0.000000 0.000000 0.020748 -0.186153
                                                                               0.000000 1992
 291 rows × 11 columns
  👺 data['NOC'].unique()
                                                               'EST',
                                                                       'MAR',
      array(['CHN', 'DEN', 'FIN', 'NOR', 'ROU', 'NED',
                      'EGY',
                                                               'AZE',
                                                                       'SUD',
                              'IRI', 'BUL',
                                              'ITA', 'CHA',
               'ARG', 'CUB', 'CMR',
                                       'TUR', 'CHI', 'GRE', 'MEX',
                                                                       'URS',
                               'ALG', 'KUW', 'BRN', 'PAK',
                      'NGR',
                                                               'IRQ',
                                                                       'UAR',
               'QAT', 'MAS', 'GER', 'RSA', 'CAN', 'USA', 'TAN', 'TUN', 'LBA',
               'DJI'], dtype=object)
[130] data_WOE_ENC['NOC'].unique()
       array([-0.72514991, 0.33572205, -0.35742513,
                                                            0.
                                                                          -0.72514991,
               -2.22922731, -1.8237622 , -0.11901411, 0.12214795, 0.16036916,
               -0.03200273, 0.37346238, -1.8237622 , -3.43<u>320011, -1.41829709</u>,
               -0.21432429, -1.13061502, 1.17197007])
def check_woe_encoding(field):
  data\_ones = data[data['Sex'] == 1].shape[0]
  data\_zeros = data[data['Sex'] == 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['Sex'] == 1].shape[0]
       filter_data_zeros = data_filter[data_filter['Sex'] == 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('Medal')

Gold - 0.33135713595444244

Bronze - -1.0185695809945734

Silver - -1.8658674413817768
```

ящик с усами

Обнаружение и удаление выбросов на основе правила трех сигм

```
[148]
                                                   0 сек.
 import numpy as np
 import pandas as pd
 import seaborn as sns
 import matplotlib.pyplot as plt
 import scipy.stats as stats
 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")
[149]
                                                   0 сек.
 def diagnostic_plots(df, variable, title):
   fig, ax = plt.subplots(figsize=(10,7))
   # гистограмма
   plt.subplot(2, 2, 1)
   df[variable].hist(bins=30)
   ## Q-Q plot
   plt.subplot(2, 2, 2)
   stats.probplot(df[variable], dist="norm", plot=plt)
```

```
plt.subplot(2, 2, 3)
sns.violinplot(x=df[variable])
# ящик с усами
plt.subplot(2, 2, 4)
sns.boxplot(x=df[variable])
fig.suptitle(title)
plt.show()
```

[150]

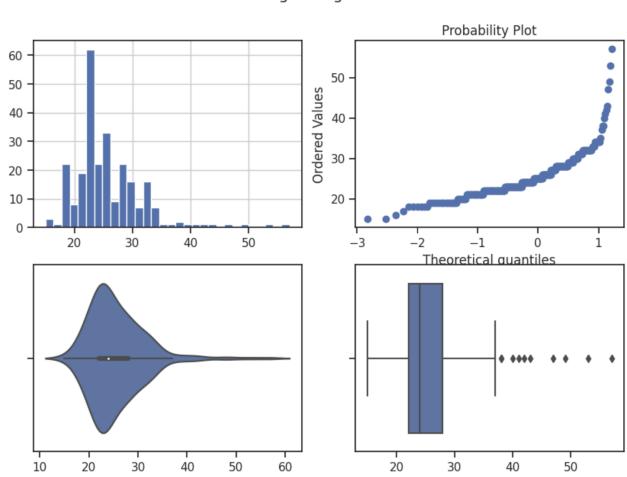
3 сек.

diagnostic_plots(data, 'Age', 'Age - original')

[151]

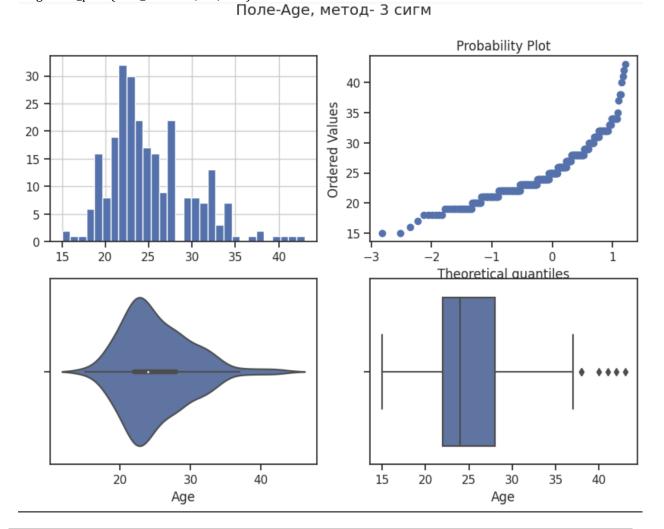
0 сек.

Age - original



Функция вычисления верхней и нижней границы выбросов def get_outlier_boundaries(df, col):

Удаление выбросов



Для произвольной колонки данных построить график "Скрипичная диаграмма (violin plot)".

[135] 0 cek.

sns.violinplot(x='Year', data=data)

