Саргсян Тигран ИУ5-62Б

Рубежный контроль №1

20 Вариант

Задача №3

Для заданного набора данных произведите масштабирование данных (для одного признака) и преобразование категориальных признаков в количественные двумя способами (label encoding, one hot encoding) для одного признака. Какие методы Вы использовали для решения задачи и почему?

Дополнение для ИУ5-62Б.

Для произвольной колонки данных построить гистограмму.

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

In [8]:
data=pd.read_csv("states_all.csv")

data.head()

Out[9]:

	PRIMARY_KEY	STATE	YEAR	ENROLL	TOTAL_REVENUE	FEDERAL_REVENUE	STATE_REVENUE	LOCAL_REVENUE	TOTAL_EXPENDITURI
0	1992_ALABAMA	ALABAMA	1992	NaN	2678885.0	304177.0	1659028.0	715680.0	2653798.(
1	1992_ALASKA	ALASKA	1992	NaN	1049591.0	106780.0	720711.0	222100.0	972488.0
2	1992_ARIZONA	ARIZONA	1992	NaN	3258079.0	297888.0	1369815.0	1590376.0	3401580.0
3	1992_ARKANSAS	ARKANSAS	1992	NaN	1711959.0	178571.0	958785.0	574603.0	1743022.0
4	1992_CALIFORNIA	CALIFORNIA	1992	NaN	26260025.0	2072470.0	16546514.0	7641041.0	27138832.(

5 rows × 25 columns

<u>▶</u>
In [10]:

типы колонок data.dtypes

```
Out[10]:
PRIMARY_KEY
                                     object
STATE
                                     object
YEAR
ENROLL
                                    float64
TOTAL REVENUE
                                   float64
FEDERAL REVENUE
                                    float64
STATE REVENUE
                                   float64
LOCAL REVENUE
                                   float64
TOTAL EXPENDITURE
                                   float64
INSTRUCTION EXPENDITURE
                                  float64
SUPPORT_SERVICES_EXPENDITURE
                                   float64
OTHER EXPENDITURE
                                   float64
CAPITAL_OUTLAY_EXPENDITURE
                                   float64
GRADES PK G
                                   float64
GRADES_KG_G
                                    float64
GRADES_4_G
                                    float64
GRADES 8 G
                                    float64
GRADES 12 G
                                   float.64
GRADES 1 8 G
                                   float64
GRADES 9 12 G
                                   float64
GRADES_ALL_G
                                   float64
AVG MATH 4_SCORE
                                   float64
AVG MATH 8 SCORE
                                   float64
AVG READING 4 SCORE
                                   float64
AVG READING 8 SCORE
                                   float64
dtype: object
                                                                                                                 In [11]:
# размер набора данных
data.shape
                                                                                                                Out[11]:
(1715, 25)
Масштабирование
                                                                                                                 In [12]:
from sklearn.preprocessing import MinMaxScaler, StandardScaler
                                                                                                                 In [13]:
data.describe()
                                                                                                                Out[13]:
            YEAR
                      ENROLL TOTAL_REVENUE FEDERAL_REVENUE STATE_REVENUE LOCAL_REVENUE TOTAL_EXPENDITURE INSTRUCTION
                                                                               1.275000e+03
count 1715.000000 1.224000e+03
                                1.275000e+03
                                                 1.275000e+03
                                                                1.275000e+03
                                                                                                 1.275000e+03
      2002.075219 9.175416e+05
                                9.102045e+06
                                                 7.677799e+05
                                                                4.223743e+06
                                                                               4.110522e+06
                                                                                                 9.206242e+06
 mean
         9.568621 1.066514e+06
                                1.175962e+07
                                                 1.146992e+06
                                                                5.549735e+06
                                                                               5.489562e+06
                                                                                                 1.199279e+07
  min 1986.000000 4.386600e+04
                                4.656500e+05
                                                 3.102000e+04
                                                                0.000000e+00
                                                                               2.209300e+04
                                                                                                 4.816650e+05
  25% 1994.000000 2.645145e+05
                                2.189504e+06
                                                 1.899575e+05
                                                                1.165776e+06
                                                                               7.151210e+05
                                                                                                 2.170404e+06
      2002.000000 6.499335e+05
                                 5.085826e+06
                                                 4.035480e+05
                                                                2.537754e+06
                                                                               2.058996e+06
                                                                                                 5.242672e+06
  75% 2010.000000 1.010532e+06
                                 1.084516e+07
                                                 8.279320e+05
                                                                5.055548e+06
                                                                               4.755293e+06
                                                                                                 1.074420e+07
  max 2019.000000 6.307022e+06
                                 8.921726e+07
                                                 9.990221e+06
                                                                5.090457e+07
                                                                               3.610526e+07
                                                                                                 8.532013e+07
8 rows × 23 columns
```

Выберем для масштабирования параметр "LOCAL_REVENUE"

In [14]:

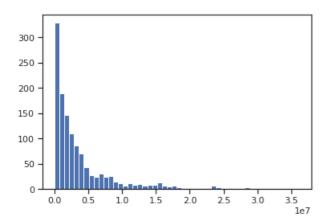
Þ

data['LOCAL REVENUE']

```
Out[14]:
         715680.0
0
         222100.0
1
        1590376.0
3
         574603.0
        7641041.0
1710
              NaN
1711
               NaN
1712
               NaN
1713
              NaN
1714
Name: LOCAL_REVENUE, Length: 1715, dtype: float64
```

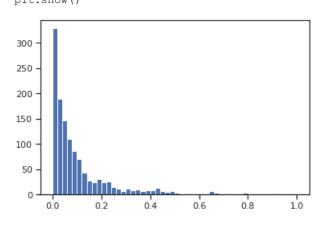
MinMax масштабирование

```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['LOCAL_REVENUE']])
                                                                                                       In [16]:
plt.hist(data['LOCAL REVENUE'][:1275], 50)
plt.show()
```



Значения лежат в диапазоне от 0 до 2.5.

```
plt.hist(sc1_data[:1275], 50)
plt.show()
```



Масштабирование данных на основе Z-оценки (StandardScaler)

```
sc2 = StandardScaler()
sc2 data = sc2.fit transform(data[['LOCAL REVENUE']])
```

В этом случае большинство значений попадает в диапазон от -0,7 до 3.

```
plt.hist(sc2 data[:1275], 50)
plt.show()
```

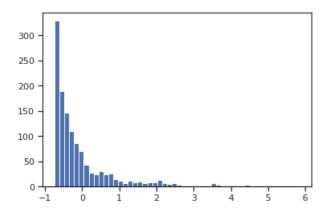
In [15]:

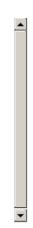


In [17]:

In [18]:

In [19]:





Преобразование категориальных признаков в количественные

label encoding

types=data["STATE"]
types.value_counts()

In [20]:

```
KANSAS
ARIZONA
                                        33
OREGON
                                       33
                                      33
COLORADO
DISTRICT_OF_COLUMBIA 33
ILLINOIS 33
NEBRASKA
                                      33
WEST_VIRGINIA 33
VERMONT 33
                                      33
 IOWA
OKLAHOMA
WYOMING
                                        33
                                      33
                                      33
MASSACHUSETTS 33
WASHINGTON 33
VIRGINIA 33
MICHIGAN 33
HAWAJT
                                      3.3
HAWATT
HAWAII 33
NEW_JERSEY 33
PENNSYLVANIA 33
NEVADA 33
TENNESSEE
                                        33
ALABAMA 33

ALABAMA 33

SOUTH_DAKOTA 33

NORTH_CAROLINA 33

MARYLAND 33

NORTH_DAKOTA 33

ARKANSAS 33

MINNESOTA 33

INDIANA 33
                                      33
INDIANA
UTAH 33
CALIFORNIA 33
NEW_HAMPSHIRE 33
IDAHO 33
NEW_MEXICO 33
LOUISIANA 33
MISSISSIPPI 33
WISCONSIN 33
KENTUCKY 33
MAINE 33
GEORGIA 33
MISSOURI 33
FLORIDA 33
TEXAS 33
                                      33
33
UTAH
                                       33
TEXAS
DODEA
NATIONAL
                                       16
Name: STATE, dtype: int64
                                                                                                                                                                      In [21]:
 le=sklearn.preprocessing.LabelEncoder()
 type le=le.fit transform(types)
 print(np.unique(type le))
 le.inverse_transform(np.unique(type_le))
 [ \ 0 \ 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 10 \ 11 \ 12 \ 13 \ 14 \ 15 \ 16 \ 17 \ 18 \ 19 \ 20 \ 21 \ 22 \ 23
  24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
  48 49 50 51 52]
                                                                                                                                                                    Out[21]:
array(['ALABAMA', 'ALASKA', 'ARIZONA', 'ARKANSAS', 'CALIFORNIA',
             'COLORADO', 'CONNECTICUT', 'DELAWARE', 'DISTRICT_OF_COLUMBIA', 'DODEA', 'FLORIDA', 'GEORGIA', 'HAWAII', 'IDAHO', 'ILLINOIS',
            'INDIANA', 'IOWA', 'KANSAS', 'KENTUCKY', 'LOUISIANA', 'MAINE', 'MARYLAND', 'MASSACHUSETTS', 'MICHIGAN', 'MINNESOTA',
            'MISSISPI', 'MISSOURI', 'MONTANA', 'NATIONAL', 'NEBRASKA',
'NEVADA', 'NEW_HAMPSHIRE', 'NEW_JERSEY', 'NEW_MEXICO', 'NEW_YORK',
'NORTH_CAROLINA', 'NORTH_DAKOTA', 'OHIO', 'OKLAHOMA', 'OREGON',
'PENNSYLVANIA', 'RHODE_ISLAND', 'SOUTH_CAROLINA', 'SOUTH_DAKOTA',
            'TENNESSEE', 'TEXAS', 'UTAH', 'VERMONT', 'VIRGINIA', 'WASHINGTON', 'WEST_VIRGINIA', 'WISCONSIN', 'WYOMING'], dtype=object)
```

Out[20]:

One hot encoding

type_s=pd.get_dummies(types)
type_s.head(25)

Out[22]: ALABAMA ALASKA ARIZONA ARKANSAS CALIFORNIA COLORADO CONNECTICUT DELAWARE DISTRICT_OF_COLUMBIA DODEA ... SOU 0 ...

25 rows × 53 columns

Гистограмма

In [23]:

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0 ...

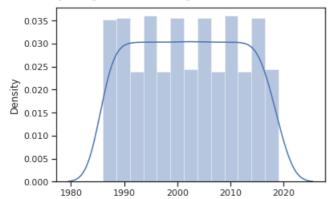
In [22]:

sns.distplot(x=data['YEAR'])

/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for h istograms).

warnings.warn(msg, FutureWarning)

<AxesSubplot:ylabel='Density'>



Out[23]:

