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

Лабораторная работа №3 по дисциплине «Технологии машинного обучения» на тему «Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных»

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1. Лабораторная работа 3

2. Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных.

2.1. Цель

изучение способов предварительной обработки данных для дальнейшего формирования моделей.

2.2. Задание:

- 1. Выбрать набор данных (датасет), содержащий категориальные 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 лекции решить следующие задачи: обработку пропусков в данных; кодирование категориальных признаков; масштабирование данных.

```
[1]: import numpy as np import pandas as pd import sklearn as sk
```

2.3. Загрузка и первичный анализ данных

```
[2]: data = pd.read_csv('fake_job_postings.csv')
[3]: data.head()
[3]:
     job_id
                                  title
                                            location \
         1
                          Marketing Intern US, NY, New York
    1
         2 Customer Service - Cloud Video Production
                                                        NZ,, Auckland
    2
         3 Commissioning Machinery Assistant (CMA)
                                                          US, IA, Wever
    3
                Account Executive - Washington DC US, DC, Washington
         4
         5
                         Bill Review Manager US, FL, Fort Worth
     department salary_range
                                                 company_profile \
    0 Marketing
                      NaN We're Food52, and we've created a groundbreaki...
       Success
                     NaN 90 Seconds, the worlds Cloud Video Production ...
    1
    2
                    NaN Valor Services provides Workforce Solutions th...
          NaN
    3
                   NaN Our passion for improving quality of life thro...
         Sales
                    NaN SpotSource Solutions LLC is a Global Human Cap...
    4
          NaN
                            description \
```

- 0 Food52, a fast-growing, James Beard Award-winn...
- 1 Organised Focused Vibrant Awesome!Do you...
- 2 Our client, located in Houston, is actively se...
- 3 THE COMPANY: ESRI Environmental Systems Rese...

4 JOB TITLE: Itemization Review ManagerLOCATION:...

```
requirements \
    0 Experience with content management systems a m...
    1 What we expect from you: Your key responsibilit...
    2 Implement pre-commissioning and commissioning ...
    3 EDUCATION: Bachelor's or Master's in GIS, busi...
    4 QUALIFICATIONS:RN license in the State of Texa...
                              benefits telecommuting \
    0
                                  NaN
    1 What you will get from usThrough being part of...
                                                               0
    2
    3 Our culture is anything but corporate—we have ...
                                                               0
    4
                       Full Benefits Offered
      has_company_logo has_questions employment_type required_experience \
    0
               1
                         0
                                 Other
                                            Internship
               1
                         0
                              Full-time
                                          Not Applicable
    1
    2
               1
                         0
                                  NaN
                                                NaN
    3
               1
                         0
                              Full-time Mid-Senior level
    4
                         1
                              Full-time
                                        Mid-Senior level
               1
     required_education
                                   industry
                                                   function \
    0
               NaN
                                 NaN
                                              Marketing
                                                 Customer Service
               NaN Marketing and Advertising
    1
    2
               NaN
                                 NaN
                                                 NaN
                              Computer Software
    3 Bachelor's Degree
                                                          Sales
    4 Bachelor's Degree
                           Hospital & Health Care Health Care Provider
      fraudulent
    0
            0
    1
            0
    2
            0
    3
            0
            0
    4
[4]: data.shape
[4]: (17880, 18)
[6]: # проверим есть ли пропущенные значения
    data.isnull().sum()
[6]: job_id
                       0
    title
                     0
    location
                      346
    department
                       11547
                       15012
    salary_range
    company_profile
                          3308
    description
                        1
```

```
2695
requirements
benefits
                7210
telecommuting
                     0
                        0
has_company_logo
has_questions
                     0
employment_type
                     3471
required_experience
                     7050
required_education
                     8105
industry
                4903
function
                 6455
fraudulent
                   0
dtype: int64
```

[7]: # типы колонок data.dtypes

[7]: job_id int64 title object location object department object salary_range object company_profile object description object requirements object benefits object telecommuting int64 has_company_logo int64 has_questions int64 employment_type object required_experience object required_education object industry object function object int64 fraudulent dtype: object

2.4. 1. Обработка пропусков в данных

```
[11]: # Удаление строк, содержащих пустые значения data_new = data.dropna(axis=0, how='any') (data.shape, data_new.shape)
```

[11]: ((17880, 18), (774, 18))

[12]: data_new.isnull().sum()

[12]: job_id 0 title 0 location 0 department 0

```
salary_range
                  0
company_profile
                     0
description
                 0
                  0
requirements
                0
benefits
                    0
telecommuting
has_company_logo
                      0
has questions
employment type
                      0
required_experience
                     0
required_education
                     0
industry
                0
                 0
function
fraudulent
                 0
dtype: int64
```

2.5. 2. Преобразование категориальных признаков в числовые

```
[19]: from sklearn.preprocessing import LabelEncoder, OneHotEncoder
[28]: le = LabelEncoder()
       cat_enc_le = le.fit_transform(data_new['required_education'])
       cat_enc_le
[28]: array([4, 1, 7, 3, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 7, 7,
            1, 1, 7, 3, 2, 3, 1, 4, 1, 7, 2, 7, 3, 2, 3, 1, 3, 6, 1, 1, 4, 1, 3,
            4, 1, 1, 1, 1, 1, 1, 1, 3, 1, 3, 7, 1, 3, 7, 1, 1, 1, 3, 1, 1, 0, 1,
            3, 1, 1, 7, 7, 3, 1, 1, 1, 1, 1, 3, 3, 0, 1, 7, 1, 3, 3, 1, 1, 7, 7,
            1, 3, 3, 1, 1, 3, 7, 1, 1, 1, 3, 1, 1, 7, 1, 7, 3, 3, 1, 1, 7, 7, 1,
            1, 8, 7, 3, 3, 1, 1, 3, 7, 3, 7, 1, 1, 7, 1, 1, 1, 1, 6, 3, 7, 0, 7,
            1, 1, 1, 1, 1, 1, 3, 1, 7, 7, 7, 3, 3, 7, 3, 1, 1, 1, 3, 1, 1, 3, 7,
            7, 7, 4, 7, 1, 3, 1, 1, 1, 7, 1, 1, 3, 1, 0, 8, 7, 7, 1, 3, 1, 1, 3,
            7, 1, 7, 1, 3, 3, 3, 3, 2, 4, 1, 3, 3, 3, 3, 3, 1, 3, 3, 1, 3, 3, 1,
            3, 1, 3, 1, 1, 1, 1, 0, 1, 1, 7, 1, 7, 7, 1, 1, 1, 1, 7, 7, 1, 4, 7,
            1, 1, 7, 7, 1, 1, 4, 7, 1, 1, 1, 3, 6, 2, 1, 3, 1, 4, 7, 3, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 7, 1, 1, 7, 3, 3, 1, 7, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
            3, 3, 3, 1, 1, 1, 1, 1, 6, 3, 1, 1, 1, 4, 3, 1, 3, 1, 1, 1, 1, 1, 1,
            1, 4, 1, 1, 1, 1, 3, 1, 1, 7, 7, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
            3, 3, 3, 3, 3, 3, 3, 4, 1, 3, 3, 3, 3, 1, 1, 1, 1, 1, 7, 3, 7,
            3, 3, 1, 1, 3, 3, 3, 1, 3, 3, 3, 1, 3, 3, 7, 1, 0, 1, 3, 6, 1, 3,
            1, 3, 1, 1, 6, 1, 6, 1, 1, 1, 4, 1, 3, 1, 3, 3, 1, 3, 1, 1, 1, 1, 8,
            1, 0, 1, 1, 3, 7, 7, 7, 3, 3, 1, 1, 1, 7, 7, 3, 3, 7, 1, 7, 1, 7, 0,
            1, 3, 1, 1, 1, 1, 1, 3, 3, 0, 1, 0, 7, 1, 1, 6, 1, 1, 7, 3, 1, 1, 4,
            1, 1, 1, 1, 3, 1, 3, 0, 1, 3, 7, 1, 3, 1, 3, 1, 1, 1, 7, 1, 7, 0, 7,
            1, 1, 1, 1, 1, 1, 8, 3, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 7, 1, 1,
            1, 1, 1, 1, 0, 0, 1, 2, 7, 1, 7, 7, 7, 0, 1, 3, 1, 3, 1, 1, 7, 1, 1,
            0, 0, 1, 7, 1, 1, 1, 7, 1, 4, 1, 1, 0, 4, 1, 1, 1, 0, 1, 3, 3, 2, 1,
            1, 3, 1, 1, 2, 2, 3, 2, 1, 7, 3, 7, 7, 1, 1, 7, 0, 9, 3, 1, 1, 2, 0,
            1, 1, 3, 5, 1, 0, 7, 0, 1, 1, 4, 3, 1, 1, 1, 3, 1, 1, 1, 7, 3, 0, 1,
```

```
3, 3, 7, 1, 1, 7, 1, 4, 7, 1, 7, 7, 3, 1, 7, 0, 1, 0, 0, 1, 3, 1, 1,
           0, 1, 1, 1, 0, 1, 1, 1, 3, 1, 7, 7, 1, 2, 7, 7, 3, 7, 3, 1, 3, 1, 1,
           1, 7, 1, 1, 1, 1, 0, 1, 7, 4, 1, 0, 3, 1, 1, 1, 1, 1, 1, 1, 0, 1, 3, 1,
           7, 1, 0, 1, 1, 1, 1, 2, 1, 3, 7, 7, 0, 1, 1, 3, 3, 1, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 7, 3, 7, 1, 0, 1, 3, 7, 1, 1, 7, 7, 5, 7, 2, 3, 1, 1,
           7, 1, 1, 3, 1, 3, 8, 7, 7, 7, 1, 1, 1, 9, 3, 3, 1, 1, 1, 5, 1, 1, 7,
           1, 3, 4, 1, 1, 1, 1, 4, 7, 7, 1, 1, 1, 1, 1, 4, 1, 2, 1, 1, 1, 7, 7,
           1, 1, 3, 1, 4, 3, 1, 7, 1, 1, 1, 7, 1, 1, 6, 1, 3, 1, 1, 7, 1, 1, 4,
           1, 1, 3, 1, 1, 1, 3, 3, 3, 3, 3, 3, 3, 1, 1])
[29]: data_new['required_education'].unique()
[29]: array(["Master's Degree", "Bachelor's Degree", 'Unspecified',
           'High School or equivalent', 'Certification',
           'Some College Coursework Completed', 'Associate Degree',
           'Vocational', 'Vocational - HS Diploma', 'Professional'], dtype=object)
[30]: np.unique(cat_enc_le)
[30]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
[31]: le.inverse_transform([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
[31]: array(['Associate Degree', "Bachelor's Degree", 'Certification',
           'High School or equivalent', "Master's Degree", 'Professional',
           'Some College Coursework Completed', 'Unspecified', 'Vocational',
           'Vocational - HS Diploma'], dtype=object)
                 Кодирование категорий наборами бинарных значений - one-hot
            encoding
```

```
[48]: ohe = OneHotEncoder()
data_encoded, data_categories = data_new['required_education'].factorize()
cat_enc_ohe = ohe.fit_transform(data_encoded.reshape(-1, 1))
cat_enc_ohe.shape

[48]: (774, 10)

[49]: data_encoded.shape

[49]: (774,)

[50]: cat_enc_ohe

[50]: <774x10 sparse matrix of type '<type 'numpy.float64'>'
with 774 stored elements in Compressed Sparse Row format>

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

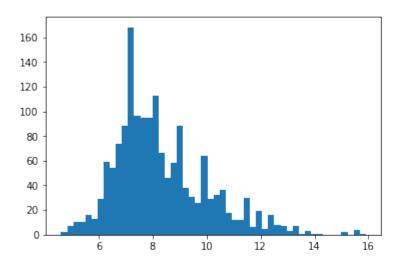
[51]: matrix([[1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],

[0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]

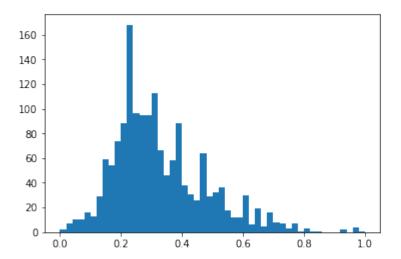
```
[0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]
           [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]
          [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]
          [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.]
          [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]
          [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]
[52]: data_categories
[52]: Index([u'Master's Degree', u'Bachelor's Degree', u'Unspecified',
          u'High School or equivalent', u'Certification',
          u'Some College Coursework Completed', u'Associate Degree',
          u'Vocational', u'Vocational - HS Diploma', u'Professional'],
         dtype='object')
     2.7. Масштабирование данных
         Для масштабирования данных будем использовать другой набор данных
[54]: data = pd.read_csv('winequality-red.csv')
[55]: data.shape
[55]: (1599, 12)
[56]: data.head()
        fixed acidity volatile acidity citric acid residual sugar chlorides \
[56]:
               7.4
                          0.70
                                    0.00
                                                1.9
                                                       0.076
      1
               7.8
                          88.0
                                    0.00
                                                2.6
                                                       0.098
      2
              7.8
                          0.76
                                    0.04
                                                2.3
                                                       0.092
      3
              11.2
                          0.28
                                                 1.9
                                                       0.075
                                    0.56
      4
              7.4
                          0.70
                                                       0.076
                                    0.00
                                                1.9
        free sulfur dioxide total sulfur dioxide density pH sulphates \
      0
                 11.0
                                 34.0 0.9978 3.51
                                                       0.56
                 25.0
                                                       0.68
      1
                                 67.0 0.9968 3.20
      2
                 15.0
                                 54.0 0.9970 3.26
                                                        0.65
      3
                 17.0
                                 60.0 0.9980 3.16
                                                        0.58
      4
                 11.0
                                 34.0 0.9978 3.51
                                                       0.56
        alcohol quality
      0
          9.4
                   5
           9.8
      1
                   5
      2
          9.8
                   5
      3
          9.8
                   6
                   5
          9.4
[57]: data.dtypes
```

[0., 0., 1., 0., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.]

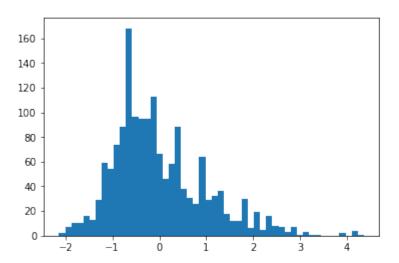
```
[57]: fixed acidity
                         float64
      volatile acidity
                          float64
      citric acid
                        float64
      residual sugar
                          float64
      chlorides
                        float64
      free sulfur dioxide
                           float64
      total sulfur dioxide float64
      density
                        float64
      pН
                       float64
      sulphates
                        float64
      alcohol
                        float64
      quality
                        int64
      dtype: object
[58]: data.isnull().sum()
                         0
[58]: fixed acidity
      volatile acidity
                          0
      citric acid
                        0
      residual sugar
                          0
      chlorides
                        0
      free sulfur dioxide
                           0
      total sulfur dioxide
      density
                       0
      pΗ
      sulphates
                        0
      alcohol
                        0
      quality
                       0
      dtype: int64
[59]: from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
[60]: sc1 = MinMaxScaler()
      sc1_data = sc1.fit_transform(data[['fixed acidity']])
[62]: import matplotlib.pyplot as plt
      %matplotlib inline
      plt.hist(data['fixed acidity'], 50)
      plt.show()
```



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



```
[65]: sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['fixed acidity']])
plt.hist(sc2_data, 50)
plt.show()
```



```
[67]: sc3 = Normalizer()
sc3_data = sc3.fit_transform(data[['fixed acidity']])
plt.hist(sc3_data, 50)
plt.show()
```

