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Рубежный контроль №1
по дисциплине
«Методы машинного обучения»

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1. Рубежный контроль №1 по дисциплине “Методы машинного обучения”

1.1. Вариант: 2, набор данных: 7

2. Загрузка и первичный анализ данных

```
In [1]: import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        %matplotlib inline
        sns.set(style='ticks')
```

```
In [2]: data = pd.read_csv('data/restaurant-scores-lives-standard.csv', sep=",
```

```
In [14]: original_size = data.shape
         print("Исходный размер:")
         print("\t- количество строк: %s" % original_size[0])
         print("\t- количество столбцов: %s" % original_size[1])
         total_count = original_size[0]
```

```
Исходный размер:
        - количество строк: 53686
        - количество столбцов: 17
```

```
In [11]: # Первые 5 строк набора
         data.head()
```

```
Out[11]:    business_id                      business_name   business_address
         0        70961  Our Lady of the Visitacion School  785 Sunnydale Ave
         1        10030         Marshall Elementary School       1575 15th St
         2        69006        Chipotle Mexican Grill #1566   50 California St
         3         5868        LONGFELLOW ELEMENTARY SCHOOL       755 MORSE St
         4         5864     VISITACION VALLEY MIDDLE SCHOOL    450 Raymond Ave

            business_city business_state business_postal_code  business_latitu
         0  San Francisco             CA                94134                 N
         1  San Francisco             CA                94103           37.7668
         2  San Francisco             CA                94111                 N
         3  San Francisco             CA                94112           37.7104
         4  San Francisco             CA                94134           37.7144

            business_longitude                                 business_locat
         0                 NaN
         1         -122.419014  {'latitude': '37.766864', 'human_address': '{"
         2                 NaN
         3         -122.447713  {'latitude': '37.710459', 'human_address': '{"
         4         -122.411433  {'latitude': '37.714428', 'human_address': '{"
```

```
  business_phone_number   inspection_id      inspection_date  \
0                   NaN  70961_20160321  2016-03-21T00:00:00
1          1.415525e+10  10030_20160321  2016-03-21T00:00:00
2                   NaN  69006_20160321  2016-03-21T00:00:00
3          1.415546e+10   5868_20160321  2016-03-21T00:00:00
4                   NaN   5864_20160321  2016-03-21T00:00:00

  inspection_score        inspection_type            violation_id  \
0            100.0  Routine - Unscheduled                     NaN
1             96.0  Routine - Unscheduled  10030_20160321_103120
2             96.0  Routine - Unscheduled  69006_20160321_103148
3             87.0  Routine - Unscheduled   5868_20160321_103154
4             94.0  Routine - Unscheduled   5864_20160321_103157

                            violation_description  risk_category
0                                             NaN            NaN
1            Moderate risk food holding temperature  Moderate Risk
2        No thermometers or uncalibrated thermometers       Low Risk
3        Unclean or degraded floors walls or ceilings       Low Risk
4  Food safety certificate or food handler card n…       Low Risk
```

```
In [12]: # Типы колонок
         data.dtypes
```

```
Out[12]: business_id                int64
         business_name             object
         business_address          object
         business_city             object
         business_state            object
         business_postal_code      object
         business_latitude        float64
         business_longitude       float64
         business_location         object
         business_phone_number    float64
         inspection_id             object
         inspection_date           object
         inspection_score         float64
         inspection_type           object
         violation_id              object
         violation_description     object
         risk_category             object
         dtype: object
```

```
In [13]: # Количество пропущенных значений в каждой колонке
         data.isnull().sum()
```

```
Out[13]: business_id                  0
         business_name                0
         business_address             0
         business_city                0
         business_state               0
```

```
business_postal_code      1241
business_latitude        24005
business_longitude       24005
business_location        24005
business_phone_number    36989
inspection_id                0
inspection_date              0
inspection_score         13947
inspection_type              0
violation_id             12946
violation_description    12946
risk_category            12946
dtype: int64
```

3. Обработка пропусков в данных

Рассматриваются колонки категориальных и количественных признаков, содержащих пропуски в данных.

Требуется выбрать одну колонку категориального признака и одну колонку количественного признака и произвести обработку пропусков в каждой из них.

```
In [16]: from sklearn.impute import SimpleImputer
         from sklearn.impute import MissingIndicator
```

3.1. Для категориального признака

```
In [15]: # Выберем категориальные колонки с пропущенными значениями
         # Цикл по колонкам датасета
         cat_cols = []
         for col in data.columns:
             # Количество пустых значений
             temp_null_count = data[data[col].isnull()].shape[0]
             dt = str(data[col].dtype)
             if temp_null_count>0 and (dt=='object'):
                 cat_cols.append(col)
                 temp_perc = round((temp_null_count / total_count) * 100.0, 2)
                 print('Колонка {}. Тип данных {}. Количество пустых значений

Колонка business_postal_code. Тип данных object. Количество пустых значений 12
Колонка business_location. Тип данных object. Количество пустых значений 24005
Колонка violation_id. Тип данных object. Количество пустых значений 12946, 24.
Колонка violation_description. Тип данных object. Количество пустых значений 1
Колонка risk_category. Тип данных object. Количество пустых значений 12946, 24
```

```
In [34]: # Фильтр по колонкам с пропущенными значениями
         data_cat = data[cat_cols]
         data_cat

Out[34]:       business_postal_code                                  business_
         0                    94134
```

```
1                    94103  {'latitude': '37.766864', 'human_address'
2                    94111
3                    94112  {'latitude': '37.710459', 'human_address'
4                    94134  {'latitude': '37.714428', 'human_address'
5                    94103  {'latitude': '37.766618', 'human_address'
6                    94109  {'latitude': '37.794298', 'human_address'
7                    94109  {'latitude': '37.792854', 'human_address'
8                    94121  {'latitude': '37.772323', 'human_address'
9                    94134  {'latitude': '37.714428', 'human_address'
10                   94109  {'latitude': '37.791683', 'human_address'
11                   94121  {'latitude': '37.782107', 'human_address'
12                   94134
13                   94134  {'latitude': '37.714428', 'human_address'
14                   94112  {'latitude': '37.710459', 'human_address'
15                   94112  {'latitude': '37.709896', 'human_address'
16                   94121  {'latitude': '37.782107', 'human_address'
17                   94111
18                   94103  {'latitude': '37.766618', 'human_address'
19                   94112  {'latitude': '37.709896', 'human_address'
20                   94121  {'latitude': '37.782107', 'human_address'
21                   94103  {'latitude': '37.766618', 'human_address'
22                   94121  {'latitude': '37.782107', 'human_address'
23                   94109  {'latitude': '37.790253', 'human_address'
24                   94134  {'latitude': '37.729016', 'human_address'
25                   94134
26                   94112  {'latitude': '37.710459', 'human_address'
27                   94112  {'latitude': '37.709896', 'human_address'
28                   94110  {'latitude': '37.754397', 'human_address'
29                   94102  {'latitude': '37.788673', 'human_address'
…                    …
53656                94112
53657                94102  {'latitude': '37.777017', 'human_address'
53658                94110
53659                94122
53660                94103  {'latitude': '37.774722', 'human_address'
53661                94111
53662                94117
53663                94110  {'latitude': '37.743206', 'human_address'
53664                94110
53665                94124
53666                94110
53667                94110
53668                94114  {'latitude': '37.767194', 'human_address'
53669                94110
53670                94103
53671                94134
53672                94114
53673                94109
53674                94133  {'latitude': '37.797868', 'human_address'
53675                94134  {'latitude': '37.715126', 'human_address'
```

```
53676                94103  {'latitude': '37.778547', 'human_address'
53677                94111  {'latitude': '37.79373', 'human_address':
53678                94111
53679                94103
53680                94124
53681                94116  {'latitude': '37.742048', 'human_address'
53682                94102
53683                94110
53684                94110
53685                94111

                violation_id  \
0                        NaN
1      10030_20160321_103120
2      69006_20160321_103148
3       5868_20160321_103154
4       5864_20160321_103157
5       5998_20160321_103109
6                        NaN
7                        NaN
8                        NaN
9       5864_20160321_103144
10                       NaN
11       551_20160321_103142
12      5869_20160321_103119
13      5864_20160321_103154
14      5868_20160321_103119
15      5955_20160321_103139
16       551_20160321_103103
17     69006_20160321_103141
18      5998_20160321_103161
19      5955_20160321_103141
20       551_20160321_103157
21      5998_20160321_103133
22       551_20160321_103124
23                       NaN
24      5827_20160321_103120
25      5869_20160321_103116
26      5868_20160321_103109
27      5955_20160321_103149
28      5999_20160322_103124
29      2926_20160322_103154
…                         …
53656  87791_20170221_103154
53657  65066_20160810_103124
53658  92662_20170921_103103
53659  77564_20161107_103119
53660   7407_20170728_103145
53661  90222_20190307_103131
53662  91984_20180206_103125
```

```
53663   3870_20190318_103144
53664  89453_20161019_103142
53665  81758_20171103_103124
53666                    NaN
53667  76441_20160517_103147
53668   4479_20180201_103131
53669  94231_20171214_103120
53670                    NaN
53671  76294_20161206_103138
53672  70184_20180313_103154
53673  86545_20160520_103138
53674   2945_20161012_103119
53675    194_20190319_103119
53676  18800_20171213_103120
53677  68826_20170222_103149
53678  86933_20160411_103131
53679  86284_20180820_103103
53680  91245_20170607_103149
53681    985_20181204_103154
53682                    NaN
53683  92662_20170921_103154
53684  97277_20180816_103154
53685  77955_20160819_103154

                                    violation_description  risk_catego
0                                                     NaN           N
1               Moderate risk food holding temperature  Moderate Ri
2         No thermometers or uncalibrated thermometers       Low Ri
3         Unclean or degraded floors walls or ceilings       Low Ri
4       Food safety certificate or food handler card n…      Low Risk
5          Unclean or unsanitary food contact surfaces      High Ri
6                                                     NaN           N
7                                                     NaN           N
8                                                     NaN           N
9        Unapproved or unmaintained equipment or utensils       Low Ri
10                                                    NaN           N
11                     Unclean nonfood contact surfaces       Low Ri
12      Inadequate and inaccessible handwashing facili…  Moderate Risk
13        Unclean or degraded floors walls or ceilings       Low Ri
14      Inadequate and inaccessible handwashing facili…  Moderate Risk
15                              Improper food storage       Low Ri
16                   High risk food holding temperature      High Ri
17       Improper food labeling or menu misrepresentation       Low Ri
18                          Low risk vermin infestation       Low Ri
19       Improper food labeling or menu misrepresentation       Low Ri
20      Food safety certificate or food handler card n…      Low Risk
21              Foods not protected from contamination  Moderate Ri
22      Inadequately cleaned or sanitized food contact…  Moderate Risk
23                                                    NaN           N
24              Moderate risk food holding temperature  Moderate Ri
```

```
25     Inadequate food safety knowledge or lack of ce…  Moderate Risk
26           Unclean or unsanitary food contact surfaces      High Ri
27     Wiping cloths not clean or properly stored or …      Low Risk
28     Inadequately cleaned or sanitized food contact…  Moderate Risk
29          Unclean or degraded floors walls or ceilings       Low Ri
…                                                    …         …
53656       Unclean or degraded floors walls or ceilings       Low Ri
53657  Inadequately cleaned or sanitized food contact…  Moderate Risk
53658                 High risk food holding temperature      High Ri
53659  Inadequate and inaccessible handwashing facili…  Moderate Risk
53660   Improper storage of equipment utensils or linens       Low Ri
53661                   Moderate risk vermin infestation  Moderate Ri
53662      Noncompliance with shell fish tags or display  Moderate Ri
53663   Unapproved or unmaintained equipment or utensils       Low Ri
53664                   Unclean nonfood contact surfaces       Low Ri
53665  Inadequately cleaned or sanitized food contact…  Moderate Risk
53666                                                NaN            N
53667                 Inadequate ventilation or lighting       Low Ri
53668                   Moderate risk vermin infestation  Moderate Ri
53669             Moderate risk food holding temperature  Moderate Ri
53670                                                NaN            N
53671  Improper storage use or identification of toxi…      Low Risk
53672       Unclean or degraded floors walls or ceilings       Low Ri
53673  Improper storage use or identification of toxi…      Low Risk
53674  Inadequate and inaccessible handwashing facili…  Moderate Risk
53675  Inadequate and inaccessible handwashing facili…  Moderate Risk
53676             Moderate risk food holding temperature  Moderate Ri
53677  Wiping cloths not clean or properly stored or …      Low Risk
53678                   Moderate risk vermin infestation  Moderate Ri
53679                 High risk food holding temperature      High Ri
53680  Wiping cloths not clean or properly stored or …      Low Risk
53681       Unclean or degraded floors walls or ceilings       Low Ri
53682                                                NaN            N
53683       Unclean or degraded floors walls or ceilings       Low Ri
53684       Unclean or degraded floors walls or ceilings       Low Ri
53685       Unclean or degraded floors walls or ceilings       Low Ri

[53686 rows x 5 columns]
```

В качестве рассматриваемого категориального признака, имеющего пропуски, выбран столбец “business_postal_code”.

Обработка пропусков производится по стратегии импьютации постоянным значением.

```
In [31]: cat_temp_data = data[['business_postal_code']]
         cat_temp_data

Out[31]:       business_postal_code
         0                    94134
         1                    94103
         2                    94111
         3                    94112
```

4	94134
5	94103
6	94109
7	94109
8	94121
9	94134
10	94109
11	94121
12	94134
13	94134
14	94112
15	94112
16	94121
17	94111
18	94103
19	94112
20	94121
21	94103
22	94121
23	94109
24	94134
25	94134
26	94112
27	94112
28	94110
29	94102
…	…
53656	94112
53657	94102
53658	94110
53659	94122
53660	94103
53661	94111
53662	94117
53663	94110
53664	94110
53665	94124
53666	94110
53667	94110
53668	94114
53669	94110
53670	94103
53671	94134
53672	94114
53673	94109
53674	94133
53675	94134
53676	94103
53677	94111
53678	94111

```
         53679                   94103
         53680                   94124
         53681                   94116
         53682                   94102
         53683                   94110
         53684                   94110
         53685                   94111

         [53686 rows x 1 columns]
```

```
In [26]: # Количество пропущенных значений в колонке
         cat_temp_data[cat_temp_data['business_postal_code'].isnull()].shape[0

Out[26]: 1241

In [19]: cat_temp_data['business_postal_code'].unique()

Out[19]: array(['94134', '94103', '94111', '94112', '94109', '94121', '94110',
                '94102', '94116', '94117', '94122', '94131', '94115', '94118',
                '94132', '94114', '94127', '94104', '94123', nan, '94108', '94
                '94107', '94124', '94105', '94013', '941033148', '94158', 'Ca'
                '94143', '95105', '94101', '94120', '94130', '941102019', '941
                '92672', 'CA', '94014', '94129', '94080', '00000', '94544', '9
                '94901', '94402', '94188', '95109', '94621', '95133', '64110',
                '95122', '94602', '94102-5917', '94124-1917', '95117', '95132'

In [43]: # Импьютация константой
         imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill
         data_imp3 = imp3.fit_transform(cat_temp_data)

In [41]: np.unique(data_imp3)

Out[41]: array(['00000', '64110', '92672', '94013', '94014', '94080', '941',
                '94101', '94102', '94102-5917', '94103', '941033148', '94104',
                '94105', '94107', '94108', '94109', '94110', '941102019', '941
                '94112', '94114', '94115', '94116', '94117', '94118', '94120',
                '94121', '94122', '94123', '94124', '94124-1917', '94127', '94
                '94130', '94131', '94132', '94133', '94134', '94143', '94158',
                '94188', '94301', '94402', '94544', '94602', '94621', '94901',
                '95105', '95109', '95117', '95122', '95132', '95133', 'CA', 'C
                'None'], dtype=object)

In [25]: # Количество обработанных значений
         data_cat_const[data_cat_const=='None'].size

Out[25]: 1241
```

3.2. Для количественного признака

```
In [27]: # Выберем числовые колонки с пропущенными значениями
         # Цикл по колонкам датасета
         num_cols = []
```

```
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений
```

```
Колонка business_latitude. Тип данных float64. Количество пустых значений 240
Колонка business_longitude. Тип данных float64. Количество пустых значений 24
Колонка business_phone_number. Тип данных float64. Количество пустых значений
Колонка inspection_score. Тип данных float64. Количество пустых значений 13947
```

```
In [28]: # Фильтр по колонкам с пропущенными значениями
         data_num = data[num_cols]
         data_num
```

```
Out[28]:      business_latitude  business_longitude  business_phone_number
         0                  NaN                 NaN                    NaN
         1            37.766864         -122.419014           1.415525e+10
         2                  NaN                 NaN                    NaN
         3            37.710459         -122.447713           1.415546e+10
         4            37.714428         -122.411433                    NaN
         5            37.766618         -122.421263           1.415587e+10
         6            37.794298         -122.421387                    NaN
         7            37.792854         -122.416114                    NaN
         8            37.772323         -122.509946                    NaN
         9            37.714428         -122.411433                    NaN
         10           37.791683         -122.420944                    NaN
         11           37.782107         -122.483631                    NaN
         12                 NaN                 NaN           1.415546e+10
         13           37.714428         -122.411433                    NaN
         14           37.710459         -122.447713           1.415546e+10
         15           37.709896         -122.448082           1.415558e+10
         16           37.782107         -122.483631                    NaN
         17                 NaN                 NaN                    NaN
         18           37.766618         -122.421263           1.415587e+10
         19           37.709896         -122.448082           1.415558e+10
         20           37.782107         -122.483631                    NaN
         21           37.766618         -122.421263           1.415587e+10
         22           37.782107         -122.483631                    NaN
         23           37.790253         -122.415357                    NaN
         24           37.729016         -122.419253           1.415546e+10
         25                 NaN                 NaN           1.415546e+10
         26           37.710459         -122.447713           1.415546e+10
         27           37.709896         -122.448082           1.415558e+10
         28           37.754397         -122.420915           1.415564e+10
         29           37.788673         -122.408524                    NaN
         …                    …                   …                      …
```

```
53656          NaN          NaN           NaN
53657    37.777017  -122.421430           NaN
53658          NaN          NaN           NaN
53659          NaN          NaN  1.415582e+10
53660    37.774722  -122.406761           NaN
53661          NaN          NaN           NaN
53662          NaN          NaN           NaN
53663    37.743206  -122.421546  1.415565e+10
53664          NaN          NaN           NaN
53665          NaN          NaN           NaN
53666          NaN          NaN           NaN
53667          NaN          NaN           NaN
53668    37.767194  -122.435576  1.415562e+10
53669          NaN          NaN           NaN
53670          NaN          NaN           NaN
53671          NaN          NaN           NaN
53672          NaN          NaN  1.415594e+10
53673          NaN          NaN  1.415545e+10
53674    37.797868  -122.407194           NaN
53675    37.715126  -122.398901  1.415546e+10
53676    37.778547  -122.410130  1.415586e+10
53677    37.793730  -122.403974           NaN
53678          NaN          NaN           NaN
53679          NaN          NaN  1.415526e+10
53680          NaN          NaN           NaN
53681    37.742048  -122.499002           NaN
53682          NaN          NaN           NaN
53683          NaN          NaN           NaN
53684          NaN          NaN           NaN
53685          NaN          NaN           NaN

       inspection_score
0                 100.0
1                  96.0
2                  96.0
3                  87.0
4                  94.0
5                  87.0
6                   NaN
7                   NaN
8                   NaN
9                  94.0
10                  NaN
11                 85.0
12                 92.0
13                 94.0
14                 87.0
15                 94.0
16                 85.0
17                 96.0
```

```
18                 87.0
19                 94.0
20                 85.0
21                 87.0
22                 85.0
23                  NaN
24                 96.0
25                 92.0
26                 87.0
27                 94.0
28                 92.0
29                 88.0
…                 …
53656               NaN
53657              72.0
53658              89.0
53659              86.0
53660              94.0
53661               NaN
53662               NaN
53663              77.0
53664              90.0
53665              75.0
53666               NaN
53667              77.0
53668              82.0
53669              85.0
53670               NaN
53671              88.0
53672               NaN
53673              76.0
53674              80.0
53675              86.0
53676              92.0
53677              79.0
53678               NaN
53679               NaN
53680               NaN
53681              72.0
53682               NaN
53683              89.0
53684              85.0
53685               NaN

[53686 rows x 4 columns]
```

В качестве рассматриваемого количественного признака, имеющего пропуски, выбран столбец “inspection_score”.

Обработка пропусков производится по стратегии импьютации наиболее частыми значениями.

```
In [37]: num_temp_data = data[['inspection_score']]
         num_temp_data

Out[37]:        inspection_score
         0                 100.0
         1                  96.0
         2                  96.0
         3                  87.0
         4                  94.0
         5                  87.0
         6                   NaN
         7                   NaN
         8                   NaN
         9                  94.0
         10                  NaN
         11                 85.0
         12                 92.0
         13                 94.0
         14                 87.0
         15                 94.0
         16                 85.0
         17                 96.0
         18                 87.0
         19                 94.0
         20                 85.0
         21                 87.0
         22                 85.0
         23                  NaN
         24                 96.0
         25                 92.0
         26                 87.0
         27                 94.0
         28                 92.0
         29                 88.0
         …                  …
         53656               NaN
         53657              72.0
         53658              89.0
         53659              86.0
         53660              94.0
         53661               NaN
         53662               NaN
         53663              77.0
         53664              90.0
         53665              75.0
         53666               NaN
         53667              77.0
         53668              82.0
         53669              85.0
         53670               NaN
         53671              88.0
```

```
        53672                 NaN
        53673                76.0
        53674                80.0
        53675                86.0
        53676                92.0
        53677                79.0
        53678                 NaN
        53679                 NaN
        53680                 NaN
        53681                72.0
        53682                 NaN
        53683                89.0
        53684                85.0
        53685                 NaN

        [53686 rows x 1 columns]

In [38]: # Количество пропущенных значений в колонке
         num_temp_data[num_temp_data['inspection_score'].isnull()].shape[0]

Out[38]: 13947

In [39]: num_temp_data['inspection_score'].unique()

Out[39]: array([ 100.,   96.,   87.,   94.,   nan,   85.,   92.,   88.,   90.,
                  98.,   83.,   76.,   80.,   93.,   57.,   91.,   68.,   86.,
                  77.,   84.,   89.,   81.,   82.,   73.,   74.,   75.,   71.,
                  79.,   78.,   69.,   72.,   70.,   63.,   67.,   61.,   66.,
                  65.,   55.,   56.,   64.,   59.,   62.,   53.,   60.,   48.,
                  58.,   45.,   51.,   54.])

In [56]: # Функция для импьютации
         def test_num_impute_col(dataset, column, strategy_param):
             temp_data = dataset[[column]]

             indicator = MissingIndicator()
             mask_missing_values_only = indicator.fit_transform(temp_data)

             imp_num = SimpleImputer(strategy=strategy_param)
             data_num_imp = imp_num.fit_transform(temp_data)

             filled_data = data_num_imp[mask_missing_values_only]

         #    return column, strategy_param, filled_data.size, filled_data[0],
             return data_num_imp, column, strategy_param, filled_data.size, fi

In [57]: data[['inspection_score']].describe()

Out[57]:        inspection_score
         count      39739.000000
         mean          85.984071
         std             8.647772
         min            45.000000
         25%            81.000000
         50%            87.000000
         75%            92.000000
         max           100.000000
```

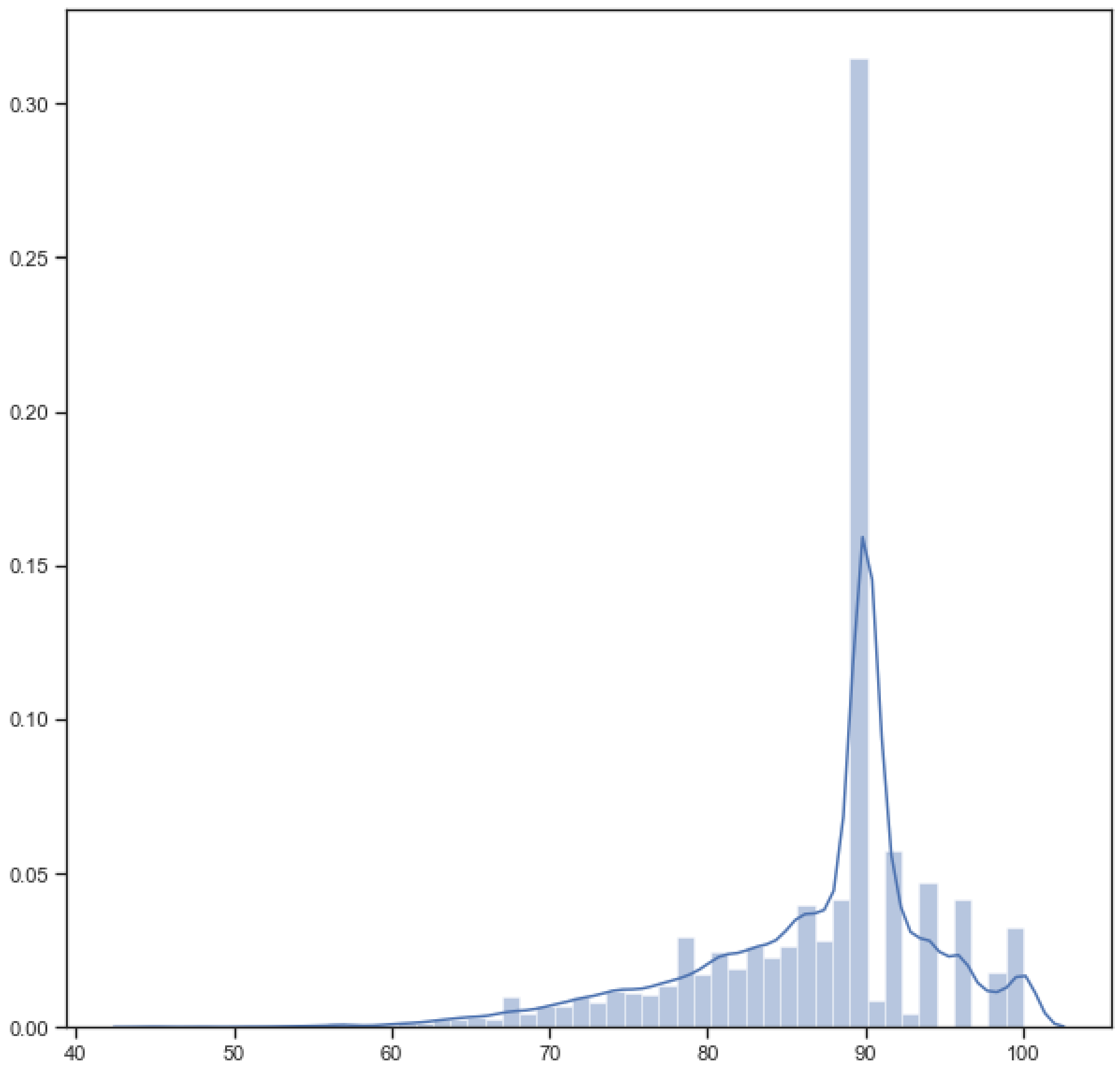
```
In [58]: data_num_imp = test_num_impute_col(data, 'inspection_score', 'most_fr
         data_num_imp
```

```
Out[58]: (array([[ 100.],
                 [  96.],
                 [  96.],
                 …,
                 [  89.],
                 [  85.],
                 [  90.]]), 'inspection_score', 'most_frequent', 13947, 90.0,
```

3.2.1. Визуализация

```
In [60]: fig, ax = plt.subplots(figsize=(10,10))
         sns.distplot(data_num_imp[0])
```

```
Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x21c41d51e10>
```


0.30
0.25
0.20
0.15
0.10
0.05
0.00
40
50
60
70
80
90
100