```
In [1]: 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")
In [2]:
        hdata = pd.read_excel('heart_disease.xlsx')
        hdata.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 303 entries, 0 to 302
        Data columns (total 14 columns):
         #
             Column
                       Non-Null Count Dtype
        - - -
             -----
                       -----
         0
             age
                       303 non-null
                                       float64
         1
             sex
                       303 non-null
                                       float64
         2
                       303 non-null
                                       float64
             ср
         3
             trestbps 303 non-null
                                       float64
         4
                       303 non-null
                                       float64
             chol
         5
             fbs
                       303 non-null
                                       float64
         6
                       303 non-null
                                       float64
             restecq
         7
             thalach
                       303 non-null
                                       float64
                       303 non-null
             exang
                                       float64
                       303 non-null
         9
             oldpeak
                                       float64
         10
             slope
                       303 non-null
                                       float64
         11 ca
                       303 non-null
                                       float64
             thal
                       303 non-null
                                       float64
         12
         13 target
                       303 non-null
                                       float64
        dtypes: float64(14)
        memory usage: 33.3 KB
In [3]: hdata.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 303 entries, 0 to 302
        Data columns (total 14 columns):
                       Non-Null Count Dtype
         # Column
        - - -
         0
                       303 non-null
                                       float64
             age
                       303 non-null
         1
             sex
                                        float64
                                       float64
         2
                       303 non-null
             ср
             trestbps 303 non-null
         3
                                       float64
         4
             chol
                       303 non-null
                                        float64
         5
                       303 non-null
                                       float64
             fbs
             restecg
         6
                       303 non-null
                                       float64
         7
             thalach
                       303 non-null
                                       float64
         8
                       303 non-null
                                        float64
             exang
         9
                       303 non-null
                                       float64
             oldpeak
         10
             slope
                       303 non-null
                                        float64
         11
                       303 non-null
                                        float64
             ca
             thal
                       303 non-null
                                       float64
         12
         13 target
                                       float64
                       303 non-null
        dtypes: float64(14)
        memory usage: 33.3 KB
In [4]: hdata.shape
        (303, 14)
Out[4]:
In [5]: hdata.head(20)
```

```
age sex cp trestbps
                                      chol fbs restecg thalach exang oldpeak slope ca thal target
            0 63.0
                    1.0 3.0
                               145.0 233.0
                                            1.0
                                                    0.0
                                                          150.0
                                                                   0.0
                                                                            23
                                                                                  0.0 0.0
                                                                                           1.0
                                                                                                  1.0
            1 37.0
                   1.0 2.0
                               130.0 250.0
                                                    1.0
                                                          187.0
                                                                   0.0
                                                                                  0.0 0.0
                                                                                           2.0
                                                                                                  1.0
            2 41.0 0.0 1.0
                               130.0 204.0 0.0
                                                    0.0
                                                          172.0
                                                                   0.0
                                                                            1.4
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
            3 56.0 1.0 1.0
                               120.0 236.0
                                           0.0
                                                    1.0
                                                          178.0
                                                                   0.0
                                                                            0.8
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
              57.0 0.0 0.0
                               120.0 354.0
                                           0.0
                                                    1.0
                                                          163.0
                                                                   1.0
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
            5 57.0 1.0 0.0
                               140.0 192.0 0.0
                                                    1.0
                                                          148.0
                                                                   0.0
                                                                            0.4
                                                                                  1.0 0.0
                                                                                           1.0
                                                                                                  1.0
            6 56.0 0.0 1.0
                               140.0 294.0
                                           0.0
                                                    0.0
                                                          153.0
                                                                   0.0
                                                                            1.3
                                                                                  1.0 0.0
                                                                                           2.0
                                                                                                  1.0
            7 44.0 1.0 1.0
                               120.0 263.0
                                                    1.0
                                                          173.0
                                                                   0.0
                                                                                  2.0 0.0
                                                                                           3.0
                                                                                                  1.0
            8 52.0 1.0 2.0
                               172.0 199.0
                                           1.0
                                                    1.0
                                                          162.0
                                                                   0.0
                                                                            0.5
                                                                                  2.0 0.0
                                                                                           3.0
                                                                                                  1.0
            9
              57.0
                   1.0 2.0
                               150.0
                                     168.0
                                           0.0
                                                    1.0
                                                          174.0
                                                                   0.0
                                                                            1.6
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
              54.0
                   1.0 0.0
                               140.0 239.0
                                           0.0
                                                    1.0
                                                          160.0
                                                                   0.0
                                                                            1.2
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
           11 48.0 0.0 2.0
                               130.0 275.0 0.0
                                                    1.0
                                                          139.0
                                                                   0.0
                                                                            0.2
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
           12
              49.0 1.0 1.0
                               130.0 266.0
                                           0.0
                                                    1.0
                                                          171.0
                                                                   0.0
                                                                            0.6
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
              64.0
                   1.0 3.0
                               110.0 211.0
                                           0.0
                                                    0.0
                                                          144.0
                                                                   1.0
                                                                            1.8
                                                                                  1.0 0.0
                                                                                           2.0
                                                                                                  1.0
           14 58.0 0.0 3.0
                               150.0 283.0
                                           1.0
                                                    0.0
                                                          162.0
                                                                   0.0
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
                                                                            1.0
           15
              50.0
                    0.0 2.0
                                120.0
                                     219.0
                                            0.0
                                                    1.0
                                                          158.0
                                                                   0.0
                                                                            1.6
                                                                                  1.0 0.0
                                                                                           2.0
                                                                                                  1.0
           16
              58.0
                   0.0 2.0
                               120.0
                                     340.0
                                           0.0
                                                    1.0
                                                          172.0
                                                                   0.0
                                                                            0.0
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
           17 66.0 0.0 3.0
                               150.0 226.0
                                           0.0
                                                    1.0
                                                          114.0
                                                                   0.0
                                                                            2.6
                                                                                  0.0 0.0
                                                                                           2.0
                                                                                                  1.0
           18
              43.0 1.0 0.0
                               150.0 247.0
                                            0.0
                                                    1.0
                                                          171.0
                                                                   0.0
                                                                            1.5
                                                                                  2.0 0.0
                                                                                           2.0
                                                                                                  1.0
           19 69.0 0.0 3.0
                               140.0 239.0 0.0
                                                          151.0
                                                                   0.0
                                                                            1.8
                                                                                  2.0 2.0 2.0
                                                                                                  1.0
 In [6]: list(zip(hdata.columns, [i for i in hdata.dtypes]))
           [('age', dtype('float64')),
 Out[6]:
            ('sex', dtype('float64')),
            ('cp', dtype('float64'))
            ('trestbps', dtype('float64')),
            ('chol', dtype('float64')),
            ('fbs', dtype('float64'))
            ('restecg', dtype('float64')),
('thalach', dtype('float64')),
            ('exang', dtype('float64')),
            ('oldpeak', dtype('float64')),
            ('slope', dtype('float64')),
            ('ca', dtype('float64')),
            ('thal', dtype('float64'))
            ('target', dtype('float64'))]
           # Колонки с пропусками
In [10]:
           hcols_with_na = [c for c in hdata.columns if hdata[c].isnull().sum() < 0]
           hcols with na
           []
Out[10]:
 In [9]:
           # Количество пропусков
           [(c, hdata[c].isnull().sum()) for c in hcols with na]
 Out[9]:
           # Доля (процент) пропусков
           [(c, hdata[c].isnull().mean()) for c in hcols with na]
Out[11]:
           # Колонки для которых удаляются пропуски
In [12]:
           hcols_with_na_temp = ['age', 'sex', 'trestbps', 'target']
           # Удаление пропусков
In [13]:
           hdata_drop = hdata[hcols_with_na_temp].dropna()
           hdata_drop.shape
           (303, 4)
           def plot_hist_diff(old_ds, new_ds, cols):
In [14]:
                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))
```

In [15]: plot_hist_diff(hdata, hdata_drop, hcols_with_na_temp)

0.2

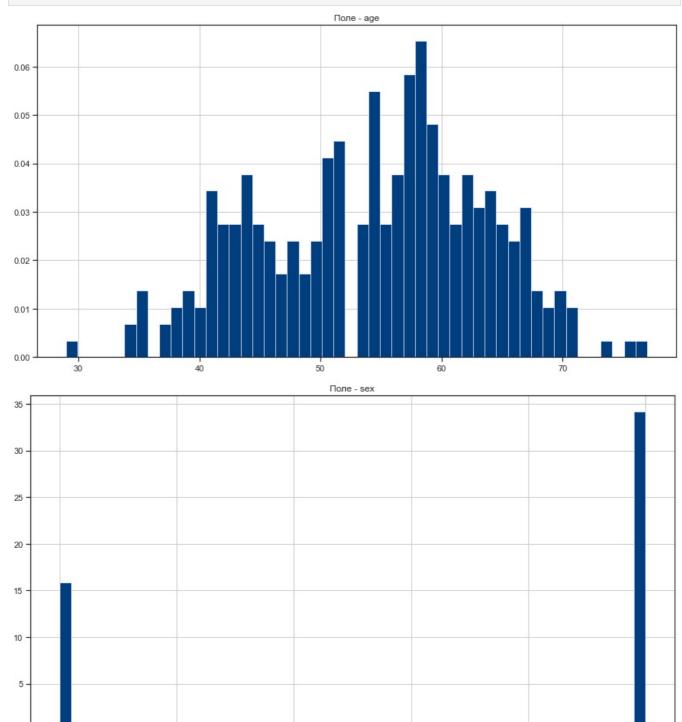
0.4

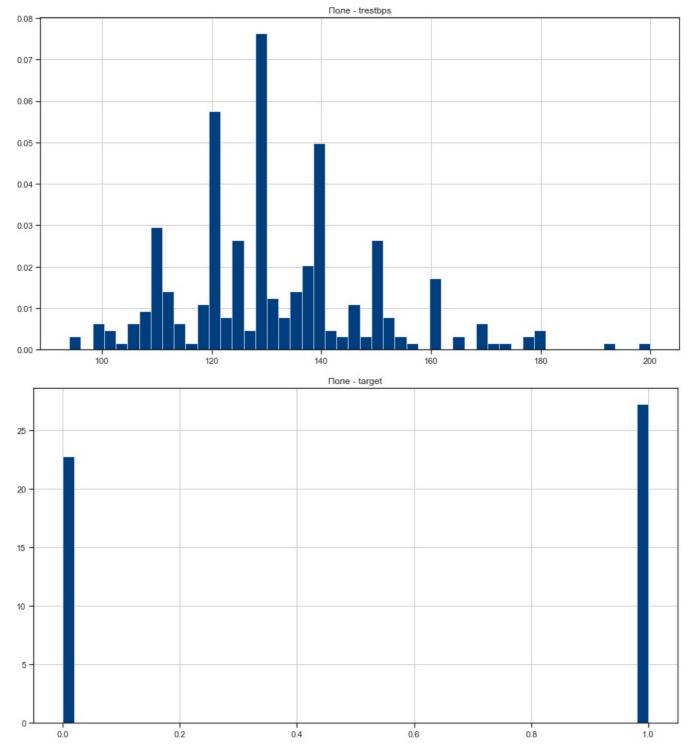
0.6

0.8

1.0

0.0



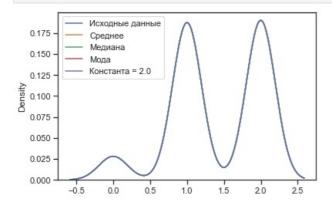


In [16]: # Пример работы MissingIndicator
temp_x1 = np.array([[np.nan, 1, 3], [4, 0, np.nan], [8, 1, 0]])
print('Исходный массив:')
print(temp_x1)

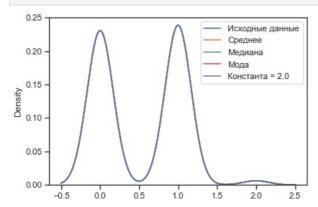
```
indicator = MissingIndicator()
             temp_x1_transformed = indicator.fit_transform(temp_x1)
             print('Маска пропущенных значений:')
            print(temp x1 transformed)
            Исходный массив:
             [[nan 1. 3.]
              [ 4. 0. nan]
              [8. 1. 0.]]
             Маска пропущенных значений:
             [[ True False]
              [False True]
              [False False]]
In [17]:
            def impute column(dataset, column, strategy param, fill value param=None):
                  Заполнение пропусков в одном признаке
                  temp data = dataset[[column]].values
                  size = temp_data.shape[0]
                  indicator = MissingIndicator()
                  mask_missing_values_only = indicator.fit_transform(temp_data)
                  imputer = SimpleImputer(strategy=strategy_param,
                                                   fill_value_fill_value_param)
                  all data = imputer.fit transform(temp data)
                  missed data = temp data[mask missing values only]
                  filled_data = all_data[mask_missing_values_only]
                  return all_data.reshape((size,)), filled_data, missed_data
In [29]:
            all data, filled data, missed data = impute column(hdata, 'thalach', 'mean')
            all data
            \mathsf{array}( \texttt{[150., 187., 172., 178., 163., 148., 153., 173., 162., 174., 160.,}
Out[29]:
                      139., 171., 144., 162., 158., 172., 114., 171., 151., 161., 179., 178., 137., 178., 162., 157., 123., 157., 152., 168., 140., 188.,
                      152., 125., 160., 170., 165., 148., 151., 142., 180., 148., 143., 182., 172., 180., 156., 115., 160., 149., 151., 146., 175., 172., 158., 186., 185., 174., 159., 130., 156., 190., 132., 165., 182.,
                      143., 175., 170., 163., 147., 154., 202., 186., 165., 161., 166., 164., 184., 154., 179., 170., 160., 178., 122., 160., 151., 156.,
                      158., 122., 175., 168., 169., 159., 138., 111., 157., 147., 162.,
                      173., 178., 145., 179., 194., 163., 115., 131., 152., 162., 159., 154., 173., 133., 161., 155., 170., 168., 162., 172., 152., 122.,
                      182., 172., 167., 179., 192., 143., 172., 169., 121., 163., 162.,
                      162., 153., 163., 163., 96., 140., 126., 105., 157., 181., 173., 142., 116., 143., 149., 171., 169., 150., 138., 125., 155., 152.,
                      152., 131., 179., 174., 144., 163., 169., 166., 182., 173., 173.,
                      108., 129., 160., 147., 155., 142., 168., 160., 173., 132., 114., 160., 158., 120., 112., 132., 114., 169., 165., 128., 153., 144.,
                      109., 163., 158., 142., 131., 113., 142., 155., 140., 147., 163., 99., 158., 177., 141., 111., 150., 145., 161., 142., 157., 139., 162., 150., 140., 140., 146., 144., 136., 97., 132., 127., 150.,
                      154., 111., 174., 133., 126., 125., 103., 130., 159., 131., 152., 124., 145., 96., 109., 173., 171., 170., 162., 156., 112., 143.,
                      132., 88., 105., 166., 150., 120., 195., 146., 122., 143., 106.,
                      125., 125., 147., 130., 126., 154., 182., 165., 160., 95., 169., 108., 132., 117., 126., 116., 103., 144., 145., 71., 156., 118.,
                      168., 105., 141., 152., 125., 125., 156., 134., 181., 138., 120.,
                      162., 164., 143., 130., 161., 140., 146., 150., 144., 144., 136., 90., 123., 132., 141., 115., 174.])
In [30]: filled data
            array([], dtype=float64)
In [31]: missed data
Out[31]: array([], dtype=float64)
            def research_impute_numeric_column(dataset, num_column, const_value=None):
    strategy_params = ['mean', 'median', 'most_frequent', 'constant']
    strategy_params_names = ['Cpeднee', 'Медиана', 'Мода']
In [32]:
                  strategy_params_names.append('Константа = ' + str(const_value))
                  original_temp_data = dataset[[num_column]].values
                  size = original temp data.shape[0]
                  original data = original temp data.reshape((size,))
                  new_df = pd.DataFrame({'Исходные данные':original_data})
                  for i in range(len(strategy params)):
                        strategy = strategy_params[i]
                        col name = strategy params names[i]
                        if (strategy!='constant') or (strategy == 'constant' and const_value!=None):
```

```
if strategy == 'constant':
          temp_data, _, _ = impute_column(dataset, num_column, strategy, fill_value_param=const_value)
else:
          temp_data, _, _ = impute_column(dataset, num_column, strategy)
          new_df[col_name] = temp_data
sns.kdeplot(data=new_df)
```

```
In [33]: research_impute_numeric_column(hdata, 'slope',2.0)
```



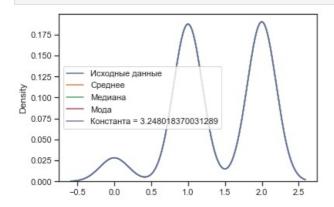
```
In [35]: research_impute_numeric_column(hdata, 'restecg',2.0)
```



```
In [36]: # Похоже на нормальное
slope_ev = hdata['slope'].mean() + 3*hdata['slope'].std()
slope_ev
```

Out[36]: 3.248018370031289

In [38]: research impute numeric column(hdata, 'slope', slope ev)



```
In [40]: # Ассиметричное
    IQR = hdata['trestbps'].quantile(0.75) - hdata['trestbps'].quantile(0.25)
    MaxTres_ev1 = hdata['trestbps'].quantile(0.75) + 3*IQR
    print('IQR={}, extreme_value={}'.format(IQR, MaxTres_ev1))

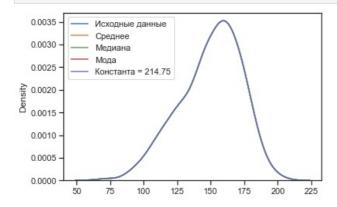
    IQR=20.0, extreme_value=200.0
```

```
In [42]: research_impute_numeric_column(hdata, 'trestbps', MaxTres_ev1)
```

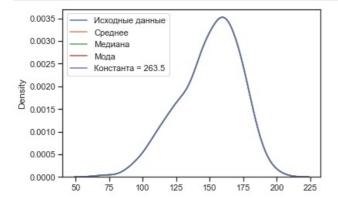
```
Среднее
   0.004
                                                      Медиана
                                                      Мода
                                                      Константа = 200.0
   0.003
Density
0.002
   0.001
   0.000
                     100
                                     140
                                              160
                                                              200
                                                                      220
                             120
                                                      180
```

```
In [45]: IQR_lf = hdata['thalach'].quantile(0.75) - hdata['thalach'].quantile(0.25)
thalach_ev1 = hdata['thalach'].quantile(0.75) + 1.5*IQR_lf
thalach_ev2 = hdata['thalach'].quantile(0.75) + 3*IQR_lf
```

In [47]: research_impute_numeric_column(hdata, 'thalach', thalach_ev1)



In [48]: research_impute_numeric_column(hdata, 'thalach', thalach_ev2)

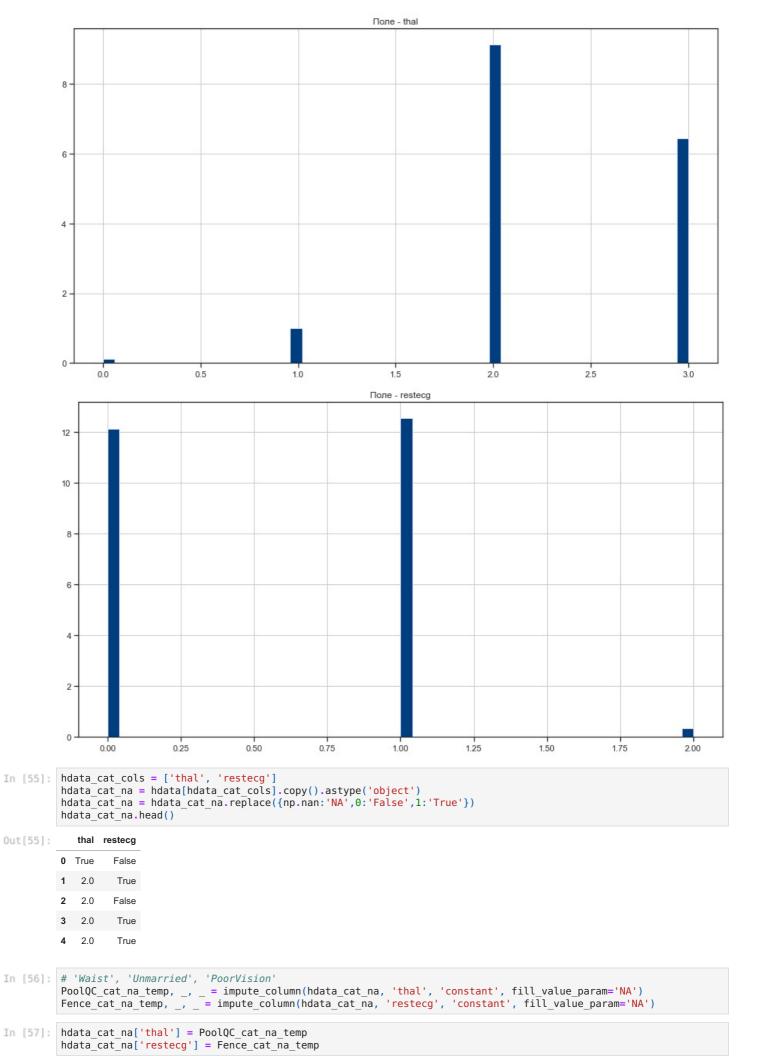


```
In [51]: # 'Unmarried',
hdata_cat_cols = ['thal', 'restecg']
hdata_cat_new = hdata[hdata_cat_cols].copy()
```

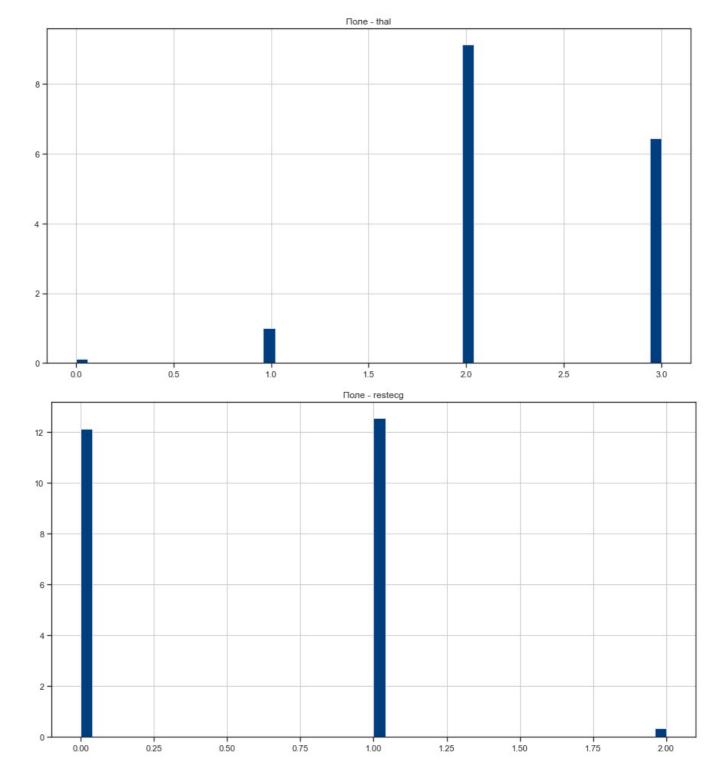
```
In [52]: PoolQC_cat_new_temp, _, _ = impute_column(hdata_cat_new, 'thal', 'most_frequent')
Fence_cat_new_temp, _, _ = impute_column(hdata_cat_new, 'restecg', 'most_frequent')
```

```
In [53]: hdata_cat_new['thal'] = PoolQC_cat_new_temp
hdata_cat_new['restecg'] = Fence_cat_new_temp
```

In [54]: plot_hist_diff(hdata, hdata_cat_new, hdata_cat_cols)



In [60]: plot_hist_diff(hdata, hdata_cat_new, hdata_cat_cols)



```
hdata_mis = hdata[['chol']].copy()
hdata_mis.head(10)
In [62]:
```

```
chol
Out[62]:
```

0 233.0

1 250.0

2 204.0

3 236.0

4 354.0

5 192.0

6 294.0

7 263.0

8 199.0

9 168.0

```
In [63]:
          indicator = MissingIndicator()
          PoolQC_missing = indicator.fit_transform(hdata_mis[['chol']])
PoolQC_missing
```

```
Out[63]: array([], shape=(303, 0), dtype=bool)
          PoolQC missing int = [1 if i==True else 0 for i in PoolQC missing]
In [64]:
          PoolQC_missing_int[:10]
          C:\Users\twail\AppData\Local\Temp\ipykernel 5384\1375431849.py:1: DeprecationWarning: The truth value of an emp
          ty array is ambiguous. Returning False, but in future this will result in an error. Use `array.size > 0` to che
          ck that an array is not empty.
           PoolQC missing int = [1 if i==True else 0 for i in PoolQC missing]
          [0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
Out[64]:
In [65]: hdata_mis['chol_missing'] = PoolQC_missing_int
          hdata mis.head()
           chol chol_missing
Out[65]:
          0 233.0
          1 250.0
                            0
          2 204.0
                            0
          3 236.0
                            0
                            0
          4 354.0
In [77]: pipe = Pipeline(steps=[
               ('imputer', KNNImputer(
                  n neighbors=5,
                   weights='distance'
                   add_indicator=False)),
               ('scaler', StandardScaler()),
               ('regressor', Lasso(max_iter=2000)),
          ])
         param_grid = {
    'imputer__n_neighbors': [4,5,6],
    'imputer__weights': ['uniform', 'distance'],
    ''autor__add_indicator': [True, False],
In [74]:
               'regressor__alpha': [10, 100, 200],
In [75]: grid_search = GridSearchCV(pipe, param_grid, cv=5, n_jobs=-1, scoring='r2')
In [79]: grid_search.fit(knnimpute_hdata, knn_hdata['Source of Care'])
          AttributeError
                                                      Traceback (most recent call last)
          Input In [79], in <cell line: 1>()
          ---> 1 grid_search.best_params_
          AttributeError: 'GridSearchCV' object has no attribute 'best_params_'
 In [ ]:
```

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js