

# Лабораторная работа №2

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## Часть 1

Цель лабораторной работы: изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

### Требования к отчету:

1) Отчет по лабораторной работе должен содержать:

- титульный лист;
- описание задания;
- текст программы;
- экранные формы с примерами выполнения программы.

2) Задание:

- Выбрать набор данных (датасет), содержащий категориальные и числовые 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.) Просьба не использовать датасет, на котором данная задача решалась в лекции.
- Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
  - устранение пропусков в данных;
  - кодирование категориальных признаков;
  - нормализацию числовых признаков.

```
In [ ]: !pip install category_encoders
        !pip install catboost
```

```
Requirement already satisfied: category_encoders in /usr/local/lib/python3.7/
dist-packages (2.2.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-
packages (from category_encoders) (1.4.1)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist
-packages (from category_encoders) (1.19.5)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-
packages (from category_encoders) (0.5.1)
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.7/dis
t-packages (from category_encoders) (1.1.5)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.
7/dist-packages (from category_encoders) (0.10.2)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python
3.7/dist-packages (from category_encoders) (0.22.2.post1)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from patsy>=0.5.1->category_encoders) (1.15.0)
```

```
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.21.1->category_encoders) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.21.1->category_encoders) (2018.9)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.0->category_encoders) (1.0.1)
Collecting catboost
  Downloading https://files.pythonhosted.org/packages/47/80/8e9c57ec32dfed6ba2922bc5c96462cbf8596ce1a6f5de532ad1e43e53fe/catboost-0.25.1-cp37-none-manylinux1_x86_64.whl (67.3MB)
    |██████████████████████████████████████| 67.3MB 65kB/s
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from catboost) (1.15.0)
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages (from catboost) (4.4.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from catboost) (3.2.2)
Requirement already satisfied: graphviz in /usr/local/lib/python3.7/dist-packages (from catboost) (0.10.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from catboost) (1.4.1)
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.7/dist-packages (from catboost) (1.1.5)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dist-packages (from catboost) (1.19.5)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist-packages (from plotly->catboost) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!<2.1.2,!<2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (1.3.1)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->catboost) (2018.9)
Installing collected packages: catboost
Successfully installed catboost-0.25.1
```

```
In [ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
In [ ]: df = pd.read_csv('aug_train.csv')
df
```

Out[ ]:	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_univers
0	8949	city_103	0.920	Male	Has relevent experience	no_enrollm
1	29725	city_40	0.776	Male	No relevent experience	no_enrollm
2	11561	city_21	0.624	NaN	No relevent experience	Full time cou
3	33241	city_115	0.789	NaN	No relevent experience	N
4	666	city_162	0.767	Male	Has relevent experience	no_enrollm
...	...	...	...	...	...	
19153	7386	city_173	0.878	Male	No relevent experience	no_enrollm

	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_univers
<b>19154</b>	31398	city_103	0.920	Male	Has relevent experience	no_enrollm
<b>19155</b>	24576	city_103	0.920	Male	Has relevent experience	no_enrollm
<b>19156</b>	5756	city_65	0.802	Male	Has relevent experience	no_enrollm
<b>19157</b>	23834	city_67	0.855	NaN	No relevent experience	no_enrollm

19158 rows × 14 columns

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 14 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   enrollee_id                          19158 non-null  int64
1   city                                 19158 non-null  object
2   city_development_index               19158 non-null  float64
3   gender                               14650 non-null  object
4   relevent_experience                  19158 non-null  object
5   enrolled_university                 18772 non-null  object
6   education_level                     18698 non-null  object
7   major_discipline                    16345 non-null  object
8   experience                           19093 non-null  object
9   company_size                        13220 non-null  object
10  company_type                         13018 non-null  object
11  last_new_job                         18735 non-null  object
12  training_hours                       19158 non-null  int64
13  target                              19158 non-null  float64
dtypes: float64(2), int64(2), object(10)
memory usage: 2.0+ MB
```

In [ ]:

```
df.isna().sum()
```

```
Out[ ]: enrollee_id      0
city                0
city_development_index  0
gender              4508
relevent_experience  0
enrolled_university  386
education_level      460
major_discipline     2813
experience           65
company_size         5938
company_type         6140
last_new_job         423
training_hours       0
target              0
dtype: int64
```

## Кодирование категориального признака

In [ ]:

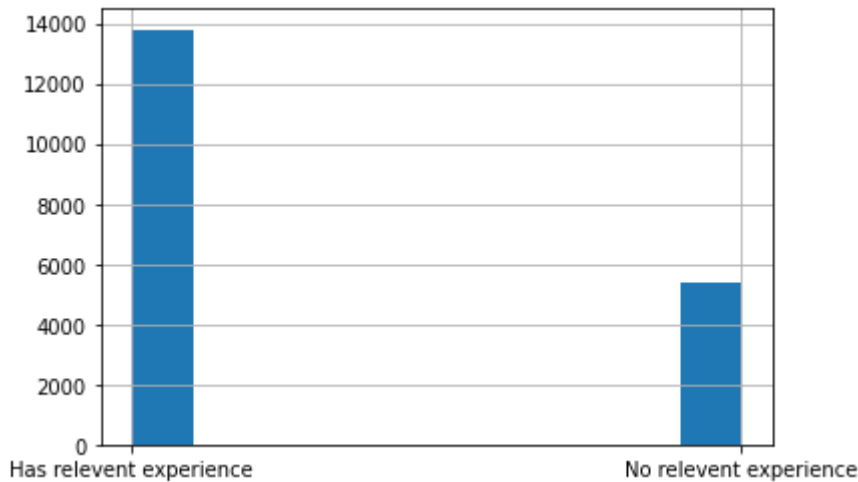
```
from category_encoders import TargetEncoder

df.relevent_experience.hist()
```

```
relevant_experience_te = TargetEncoder()
df.relevant_experience = relevant_experience_te.fit_transform(df.relevant_experience)
```

/usr/local/lib/python3.7/dist-packages/category\_encoders/utils.py:21: FutureWarning: is\_categorical is deprecated and will be removed in a future version. Use is\_categorical\_dtype instead

```
elif pd.api.types.is_categorical(cols):
```



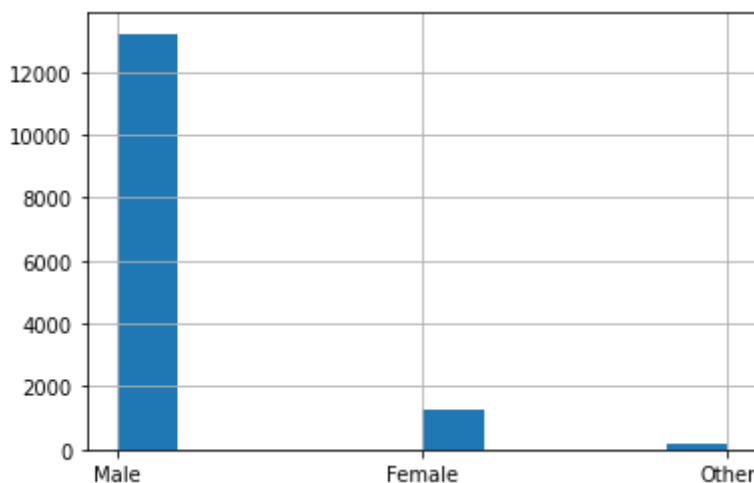
```
In [ ]: df.relevant_experience
```

```
Out[ ]: 0      0.214690
        1      0.338427
        2      0.338427
        3      0.338427
        4      0.214690
        ...
        19153  0.338427
        19154  0.214690
        19155  0.214690
        19156  0.214690
        19157  0.338427
        Name: relevant_experience, Length: 19158, dtype: float64
```

## Устранение пропусков в признаке Пол

```
In [ ]: df.gender.hist()
```

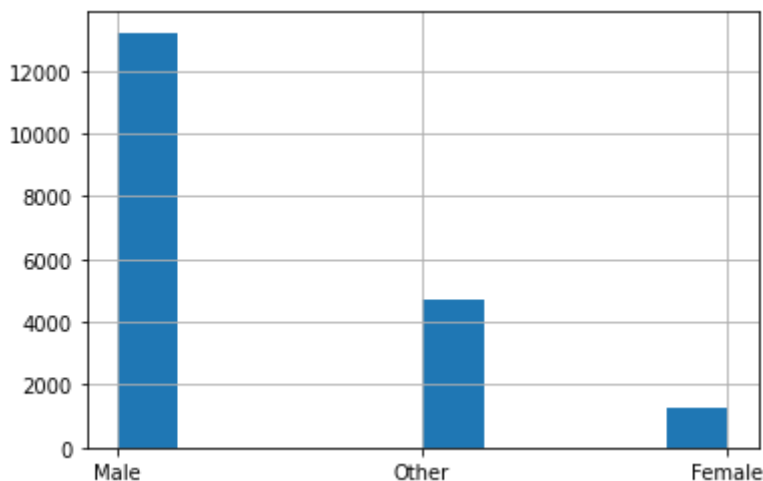
```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8601432810>
```



```
In [ ]: df.gender = df.gender.fillna('Other')
```

```
df.gender.hist()
```

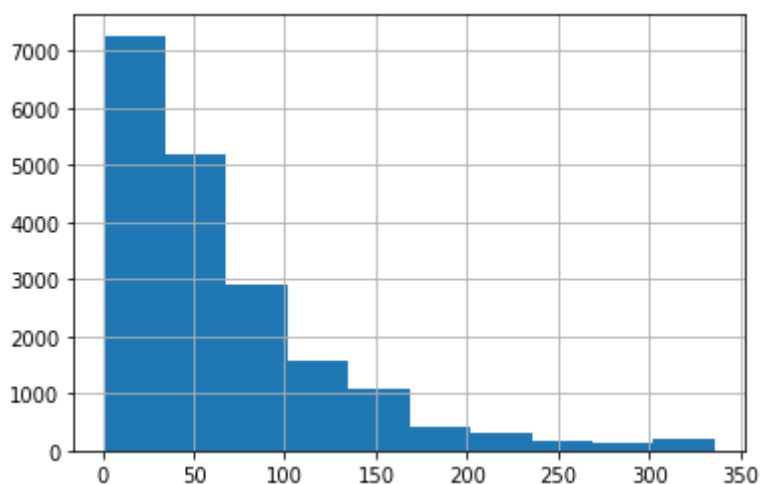
Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f86013b5890>



## Нормализация числового признака

```
In [ ]: df.training_hours.hist()
```

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f86013392d0>

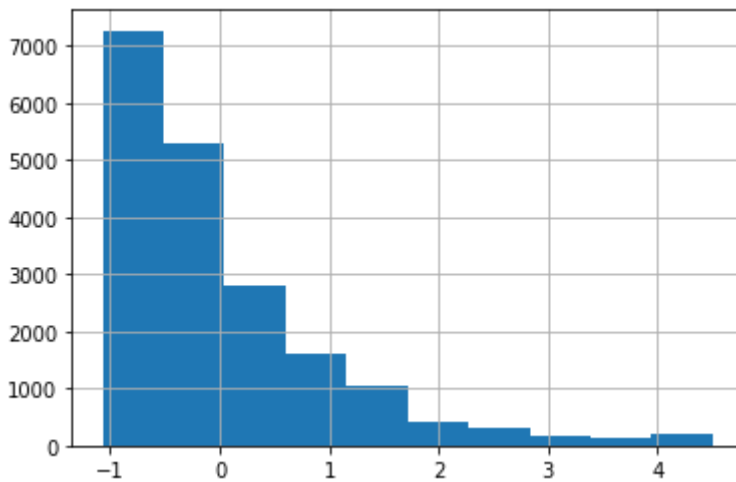


```
In [ ]: from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

df['training_hours_std_scale'] = scaler.fit_transform(np.array(df.training_ho
df.training_hours_std_scale.hist())
```

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f86012a5a10>



## Часть 2

Цель лабораторной работы: изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

### Требования к отчету:

1) Отчет по лабораторной работе должен содержать:

- титульный лист;
- описание задания;
- текст программы;
- экранные формы с примерами выполнения программы.

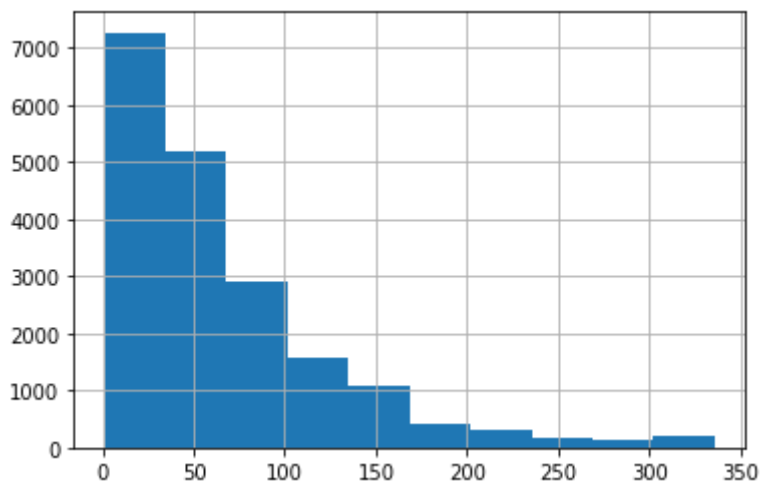
2) Задание:

- Выбрать один или несколько наборов данных (датасетов) для решения следующих задач. Каждая задача может быть решена на отдельном датасете, или несколько задач могут быть решены на одном датасете. Просьба не использовать датасет, на котором данная задача решалась в лекции.
- Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
  - масштабирование признаков (не менее чем тремя способами);
  - обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
  - обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
  - отбор признаков:
    - один метод из группы методов фильтрации (filter methods);
    - один метод из группы методов обертывания (wrapper methods);
    - один метод из группы методов вложений (embedded methods).

### Масштабируем признак несколькими способами

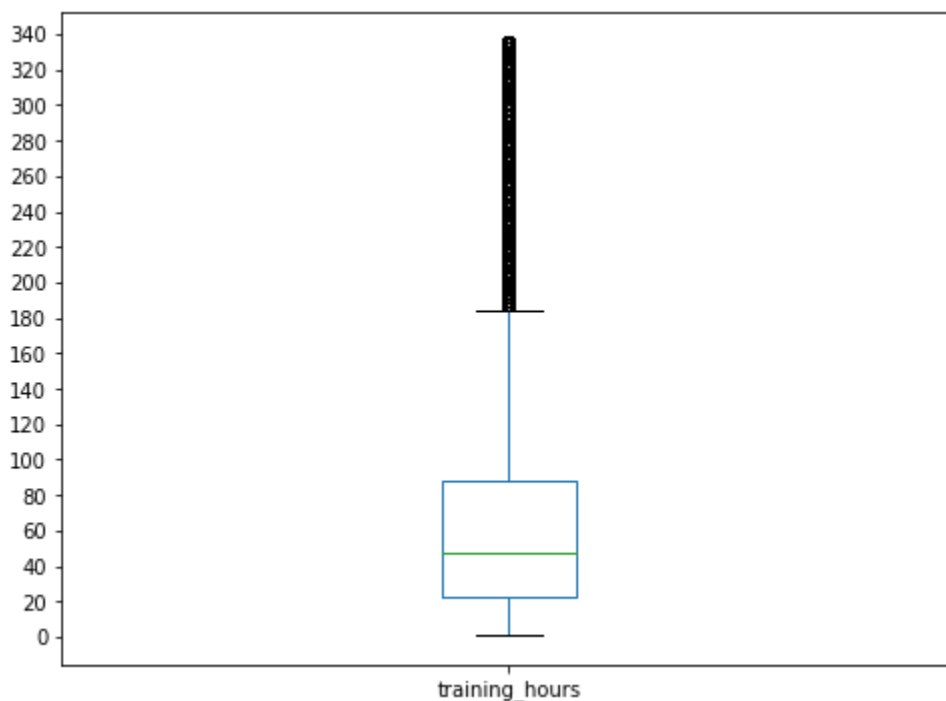
```
In [ ]: df.training_hours.hist()
```

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f86012d8f90>



### MinMaxScaling с работой с выбросами

```
In [ ]: plt.figure(figsize=(8,6))
df.training_hours.plot(kind='box')
plt.yticks(list(range(0,350, 20)))
plt.show()
```



```
In [ ]: # отбрасываем выбросы
tmp_df = df[df.training_hours < 200]
```

```
In [ ]: from sklearn.preprocessing import MinMaxScaler

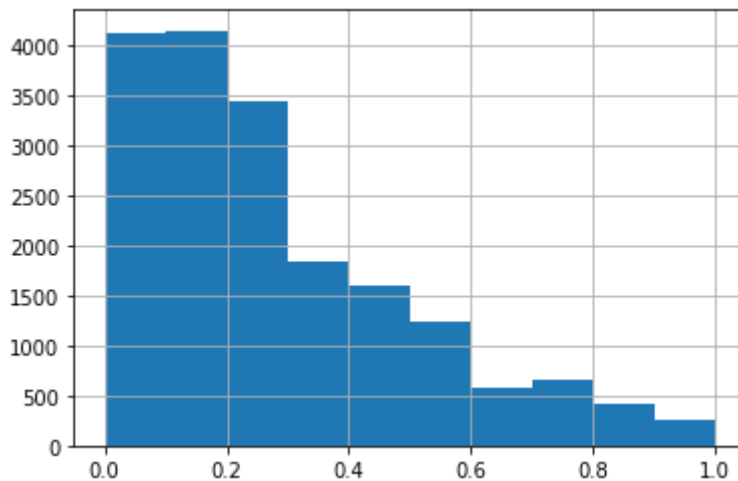
min_max = MinMaxScaler()
tmp_df.training_hours = min_max.fit_transform(np.array(tmp_df.training_hours))
tmp_df.training_hours.hist()
```

/usr/local/lib/python3.7/dist-packages/pandas/core/generic.py:5170: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.

Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
`self[name] = value`

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f86014b0650>



## MaxAbsScaler

```
In [ ]: from sklearn.preprocessing import MaxAbsScaler

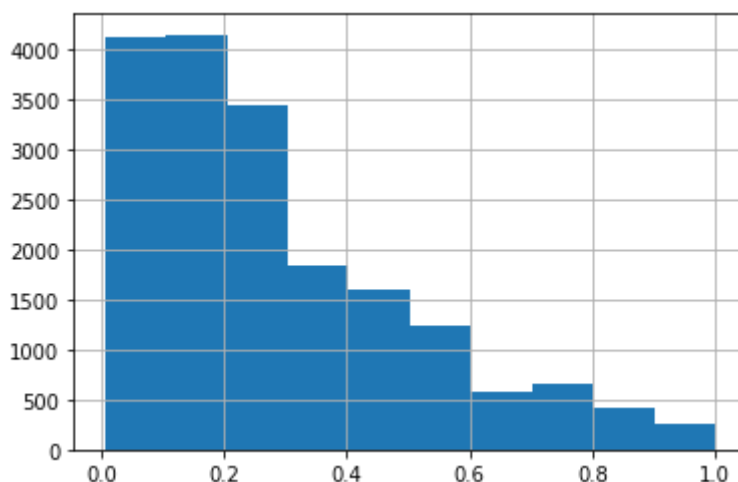
tmp_df = df[df.training_hours < 200]
min_abs = MaxAbsScaler()
tmp_df.training_hours = min_abs.fit_transform(np.array(tmp_df.training_hours))
tmp_df.training_hours.hist()
```

/usr/local/lib/python3.7/dist-packages/pandas/core/generic.py:5170: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.  
 Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
`self[name] = value`

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f8601156e10>



## RobustScaler

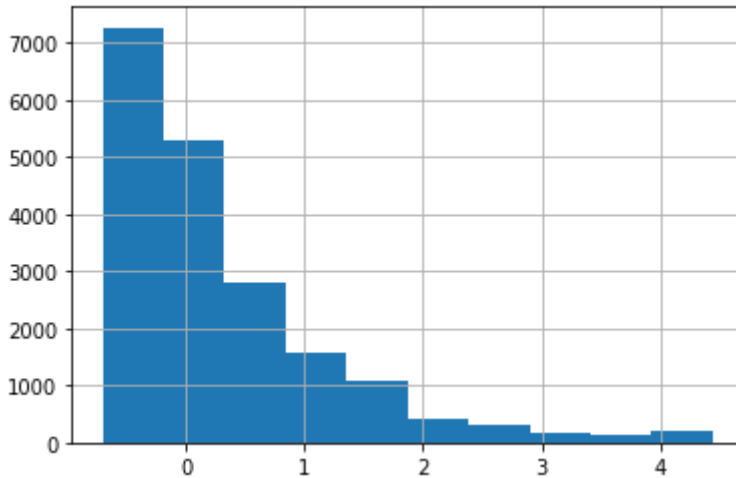
```
In [ ]: from sklearn.preprocessing import RobustScaler

robust_scaler = RobustScaler()
```



```
tmp_df = df.copy()
tmp_df['training_hours_std_scale'] = robust_scaler.fit_transform(np.array(tmp_df.training_hours_std_scale).hist())
```

Out[ ]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f8601104110>



Обработка выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);

```
In [ ]: df.experience.unique() # сделаем числовой признак из фичи experience
```

```
Out[ ]: array(['>20', '15', '5', '<1', '11', '13', '7', '17', '2', '16', '1', '4',
              '10', '14', '18', '19', '12', '3', '6', '9', '8', '20', nan],
              dtype=object)
```

```
In [ ]: df.experience = df.experience.apply(lambda x: str(x).strip('<>') if str(x) !=
```

```
In [ ]: df.experience.isna().sum() # 65 пропущенных значений
```

Out[ ]: 65

удалим строки с experience - nan

```
In [ ]: shape_before = df.shape[0]
res_df = df.dropna(subset=['experience'], inplace=False)
print(shape_before, res_df.shape[0], ', dropped', shape_before - res_df.shape
```

19158 19093 , dropped 65 rows

Заполним пропуски в том же признаке с помощью моды

```
In [ ]: print('experience mode:', df.experience.mode)
new_experience = df.experience.fillna(df.experience.mode)
print('nan values count:', new_experience.isna().sum())
```

```
experience mode: <bound method Series.mode of 0      20
1      15
2       5
3       1
4      20
..
19153   14
19154   14
```

```

19155    20
19156     1
19157     2
Name: experience, Length: 19158, dtype: object>
nan values count: 0

```

Создадим еще признак из признака company\_size этот признак будет не числовым и не категориальным

```
In [ ]: df.company_size.unique()
```

```
Out[ ]: array([nan, '50-99', '<10', '10000+', '5000-9999', '1000-4999', '10/49',
               '100-500', '500-999'], dtype=object)
```

```
In [ ]: def mean_mapper(value):
        if isinstance(value, float): # если значение пропущено вернем его же
            return np.nan
        if '-' in value:
            low, high = [int(i) for i in value.strip().split('-')]
            return (high-low)/2
        if '/' in value:
            low, high = [int(i) for i in value.strip().split('/')]
            return (high-low)/2
        if '<' in value or '>' in value:
            return int(str(value).strip('<>'))
```

```
In [ ]: df.company_size.unique()
```

```
Out[ ]: array([nan, '50-99', '<10', '10000+', '5000-9999', '1000-4999', '10/49',
               '100-500', '500-999'], dtype=object)
```

```
In [ ]: df['company_size_numeric'] = df.company_size.apply(mean_mapper)
df.company_size_numeric = df.company_size_numeric.fillna(df.company_size_numeric)
```

```
In [ ]: df.company_size_numeric.unique()
```

```
Out[ ]: array([ 438.60940987,  24.5      ,  10.      , 2499.5      ,
               1999.5      ,  19.5      ,  200.      ,  249.5      ])
```

## Отбор признаков

Закодируем все признаки в численные

```
In [ ]: df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 16 columns):
 #   Column                                Non-Null Count  Dtype
---  -
 0   enrollee_id                          19158 non-null  int64
 1   city                                  19158 non-null  object
 2   city_development_index               19158 non-null  float64
 3   gender                                19158 non-null  object
 4   relevent_experience                  19158 non-null  float64
 5   enrolled_university                 18772 non-null  object
 6   education_level                     18698 non-null  object
 7   major_discipline                    16345 non-null  object
 8   experience                           19093 non-null  object

```

```

9    company_size      13220 non-null    object
10   company_type      13018 non-null    object
11   last_new_job       18735 non-null    object
12   training_hours     19158 non-null    int64
13   target             19158 non-null    float64
14   training_hours_std_scale 19158 non-null    float64
15   company_size_numeric 19158 non-null    float64
dtypes: float64(5), int64(2), object(9)
memory usage: 2.3+ MB

```

```
In [ ]: df.gender.dtype
```

```
Out[ ]: dtype('O')
```

```
In [ ]: from category_encoders import TargetEncoder
from sklearn.preprocessing import LabelEncoder

encoders = {}

for col in df.columns:
    if df[col].dtype == 'O' and len(df[col].unique()) >= 4:
        tmp_enc = TargetEncoder()
        encoders[str(col)+'_te'] = tmp_enc
        df[col] = tmp_enc.fit_transform(df[col], df.target)
    elif len(df[col].unique()) < 4 and df[col].dtype == 'O':
        tmp_enc = LabelEncoder()
        encoders[str(col)+'_le'] = tmp_enc
        df[col] = tmp_enc.fit_transform(df[col])

X = df[[i for i in df.columns if i != 'target']]
y = df.target
```

```

/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):
/usr/local/lib/python3.7/dist-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.
Use is_categorical_dtype instead
    elif pd.api.types.is_categorical(cols):

```

## Метод фильтрации связанный с статистическими характеристиками

```
In [ ]: from sklearn.feature_selection import SelectKBest, chi2

res = SelectKBest().fit(X, y)

selected_features = [name for name, mask in zip(X.columns, res.get_support())
print(selected_features)]
```

['city', 'city\_development\_index', 'relevent\_experience', 'enrolled\_university', 'education\_level', 'major\_discipline', 'experience', 'company\_size', 'company\_type', 'last\_new\_job']

## Метод обертывания

```
In [ ]: !pip install mlxtend
```

Requirement already satisfied: mlxtend in /usr/local/lib/python3.7/dist-packages (0.14.0)  
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.7/dist-packages (from mlxtend) (0.22.2.post1)  
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from mlxtend) (1.19.5)  
Requirement already satisfied: scipy>=0.17 in /usr/local/lib/python3.7/dist-packages (from mlxtend) (1.4.1)  
Requirement already satisfied: matplotlib>=1.5.1 in /usr/local/lib/python3.7/dist-packages (from mlxtend) (3.2.2)  
Requirement already satisfied: pandas>=0.17.1 in /usr/local/lib/python3.7/dist-packages (from mlxtend) (1.1.5)  
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from mlxtend) (54.2.0)  
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.18->mlxtend) (1.0.1)  
Requirement already satisfied: cycloper>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=1.5.1->mlxtend) (0.10.0)  
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=1.5.1->mlxtend) (2.4.7)  
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=1.5.1->mlxtend) (1.3.1)  
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=1.5.1->mlxtend) (2.8.1)  
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.17.1->mlxtend) (2018.9)  
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from cycloper>=0.10->matplotlib>=1.5.1->mlxtend) (1.15.0)

```
In [ ]: from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=5)

efs1 = EFS(knn,
            min_features=2,
            max_features=3,
            scoring='roc_auc',
            print_progress=True,
            cv=5, n_jobs=-1)

efs1 = efs1.fit(X, y)

print('Best accuracy score: %.2f' % efs1.best_score_)
print('Best subset (indices):', efs1.best_idx_)
print('Best subset (corresponding names):', efs1.best_feature_names_)
```

```

Features: 560/560
Best accuracy score: 0.75
Best subset (indices): (2, 7, 9)
Best subset (corresponding names): ('city_development_index', 'major_discipline', 'company_size')

```

## Метод вложений

```

In [ ]: from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, title, figsize=(7,4)):
    """
    Вывод важности признаков в виде графика!
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    # Названия признаков
    labels = [x for x, _ in sorted_list]
    # Важности признаков
    data = [x for _, x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ax.set_title(title)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a, b in zip(ind, data):
        plt.text(a-0.1, b+0.005, str(round(b,3)))
    plt.show()
    return labels, data

```

```

In [ ]: from catboost import CatBoostClassifier
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.05, random_state=42)

cat_clf = CatBoostClassifier(random_state=42, iterations=2000, early_stopping=True)
cat_clf.fit(X_train, y_train, eval_set=(X_val, y_val))

res = np.array(sorted([(n, float(f)) for n, f in zip(X_train.columns, cat_clf.feature_importances_)])

plt.figure(figsize=(12, 6))
plt.bar(res[:,0], res[:,1])
plt.title('CatBoost feature importances')
plt.xticks(res[:,0], rotation=80)
plt.show()

```

