Лабораторная работа 2. Выполнил Зоров Владислав Витальевич ИУ5-22м

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.

311 service requests NYC (датасет) //www.kaggle.com/datasets/sheikmohamed/nyc-311-service-requests-for-2009

In [61]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
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")
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[61], line 17
     15 from sklearn.impute import IterativeImputer
     16 from IPython.display import Image
---> 17 from category_encoders.one_hot import OneHotEncoder as ce_OneHotEncoder
     18 get_ipython().run_line_magic('matplotlib', 'inline')
     19 sns.set(style="ticks")

ModuleNotFoundError: No module named 'category_encoders'
```

In [3]:
```
# Загрузка данных из csv-файла
dataset = pd.read_csv(r'C:\Users\User\Desktop\маг 2сем\гапан\2лаба\311.csv')
dataset = dataset.sample(frac=0.01)
dataset.head()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_5036\857819137.py:2: DtypeWarning: Columns (48,
49) have mixed types. Specify dtype option on import or set low_memory=False.
  dataset = pd.read_csv(r'C:\Users\User\Desktop\маг 2сем\гапан\2лаба\311.csv')
```

Out[3]:

	Unique Key	Created Date	Closed Date	Agency	Agency Name	Complaint Type	Descriptor	Location Type	Incident Zip

	Unique Key	Created Date	Closed Date	Agency	Agency Name	Complaint Type	Descriptor	Location Type	Incident Zip
192819	31010915	07/06/2015 12:16:19 PM	07/06/2015 03:37:28 PM	NYPD	New York City Police Department	Animal Abuse	Other (complaint details)	Residential Building/House	10464.0
9654	32240080	12/20/2015 11:58:51 PM	12/21/2015 07:41:28 AM	NYPD	New York City Police Department	Noise - Street/Sidewalk	Loud Music/Party	Street/Sidewalk	10467.0
77616	31766891	10/16/2015 05:36:58 PM	10/17/2015 06:30:32 AM	NYPD	New York City Police Department	Blocked Driveway	No Access	Street/Sidewalk	11377.0
144357	31336497	08/18/2015 11:01:53 PM	08/19/2015 01:03:09 AM	NYPD	New York City Police Department	Posting Advertisement	Vehicle	Street/Sidewalk	10312.0
280552	30438163	04/20/2015 04:43:02 PM	04/21/2015 01:12:45 AM	NYPD	New York City Police Department	Illegal Parking	Blocked Hydrant	Street/Sidewalk	11229.0

5 rows × 53 columns

In [4]:
```
len(list(zip(dataset.columns, [i for i in dataset.dtypes])))
# список столбцов
```

Out[4]:
```
53
```

In [5]:
```
cols_with_na = [c for c in dataset.columns if dataset[c].isnull().sum() > 0]
len(cols_with_na)
# список столбцов с пропусками
```

Out[5]:
```
31
```

In [6]:
```
dataset.shape
```

Out[6]:
```
(3646, 53)
```

In [7]:
```
[(c, dataset[c].isnull().mean()) for c in cols_with_na]
# список столбцов с процент пропусков
```

Out[7]:
```
[('Closed Date', 0.006856829402084476),
 ('Descriptor', 0.020844761382336808),
 ('Location Type', 0.0005485463521667581),
 ('Incident Zip', 0.00877674163466813),
 ('Incident Address', 0.14454196379594075),
 ('Street Name', 0.14454196379594075),
 ('Cross Street 1', 0.15962698848052662),
 ('Cross Street 2', 0.16154690071311026),
 ('Intersection Street 1', 0.8554580362040592),
 ('Intersection Street 2', 0.857377948436643),
 ('Address Type', 0.009325287986834888),
 ('City', 0.00877674163466813),
 ('Landmark', 0.9994514536478333),
 ('Facility Type', 0.006856829402084476),
 ('Resolution Action Updated Date', 0.006856829402084476),
 ('X Coordinate (State Plane)', 0.012616566099835436),
```

```
('Y Coordinate (State Plane)', 0.012616566099835436),
('School or Citywide Complaint', 1.0),
('Vehicle Type', 1.0),
('Taxi Company Borough', 1.0),
('Taxi Pick Up Location', 1.0),
('Bridge Highway Name', 0.9994514536478333),
('Bridge Highway Direction', 0.9994514536478333),
('Road Ramp', 0.9994514536478333),
('Bridge Highway Segment', 0.9994514536478333),
('Garage Lot Name', 1.0),
('Ferry Direction', 1.0),
('Ferry Terminal Name', 1.0),
('Latitude', 0.012616566099835436),
('Longitude', 0.012616566099835436),
('Location', 0.012616566099835436)]
```

In [8]:

```
# разделение столбцов на удаляемые, сокращаемые и дополняемые
cols_with_na = dataset.columns[dataset.isnull().mean() > 0].tolist()

# на удаление колонки
cols_to_drop = []
# на удаление строк
rows_to_drop = []
# на дополнение
cols_to_impute = []

for c in cols_with_na:
    na_percentage = dataset[c].isnull().mean()
    if na_percentage > 0.3:
        cols_to_drop.append(c)
    elif na_percentage < 0.06:
        rows_to_drop.append(c)
    else:
        cols_to_impute.append(c)

len(cols_to_drop), len(rows_to_drop), len(cols_to_impute)
```

Out[8]:

```
(14, 13, 4)
```

In [38]:

```
# удаляем колонки по списку
res = dataset.drop(cols_to_drop, axis=1)

# удаляем строки по сприскy
res = res.dropna(subset = rows_to_drop)

res.shape, dataset.shape
```

Out[38]:

```
((3521, 42), (3646, 53))
```

In [10]:

```
# для иллюстрации
data_drop = dataset[rows_to_drop].dropna()
data_drop.shape
```

Out[10]:

```
(3521, 13)
```

In [11]:

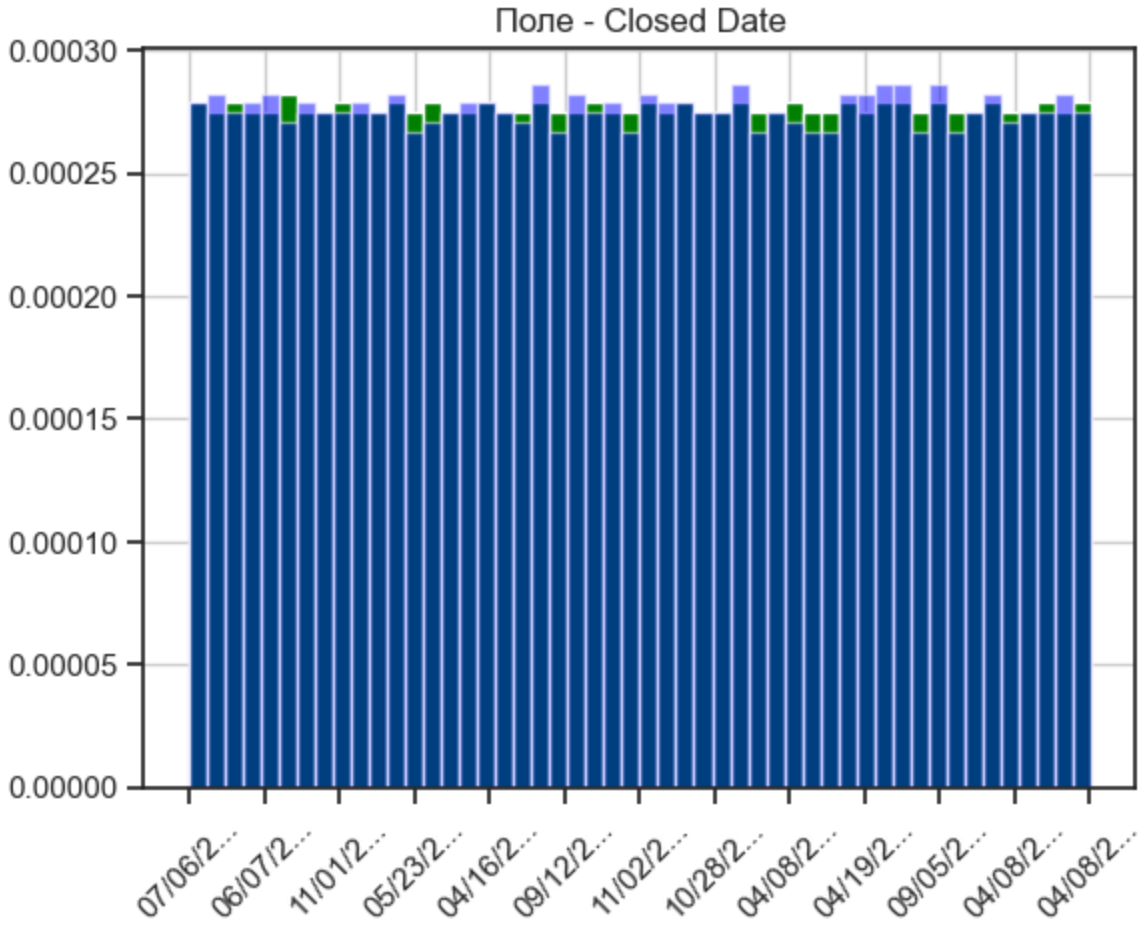
```
def plot_hist_diff(old_ds, new_ds, cols, max_xticks=12):
    """
    Разница между распределениями до и после устранения пропусков
    """
    for c in cols:
        fig = plt.figure()
```

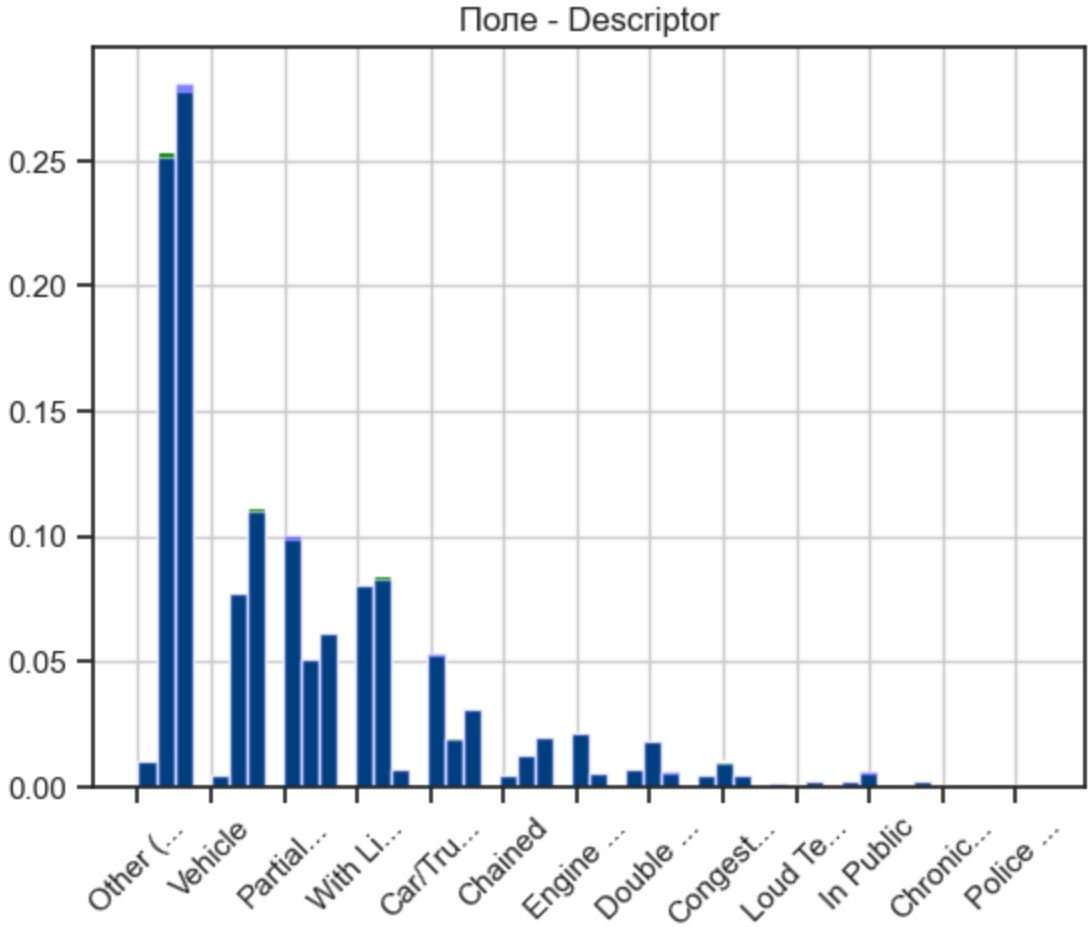
```
        ax = fig.add_subplot(111)
        ax.title.set_text('Поле - ' + str(c))
        old_ds[c].hist(bins=50, ax=ax, density=True, color='green')
        new_ds[c].hist(bins=50, ax=ax, color='blue', density=True, alpha=0.5)

        xtick_labels = ax.get_xticklabels()

        if len(xtick_labels) > max_xticks:
            xticks = ax.get_xticks()

            step = len(xticks) // max_xticks

            xticks_visible = xticks[::step]

            ax.set_xticks(xticks_visible)

            xtick_labels_new = []
            for label in ax.get_xticklabels():
                if len(label.get_text()) > 10:
                    label_text = label.get_text()[:7] + '...'
                else:
                    label_text = label.get_text()
                label_new = matplotlib.text.Text(x=label.get_position()[0],
                                                 y=label.get_position()[1],
                                                 text=label_text,
                                                 fontproperties=label.get_fontproperties
                                                 rotation=label.get_rotation(),
                                                 ha='right')
                xtick_labels_new.append(label_new)

            ax.set_xticklabels(xtick_labels_new)

        ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
```

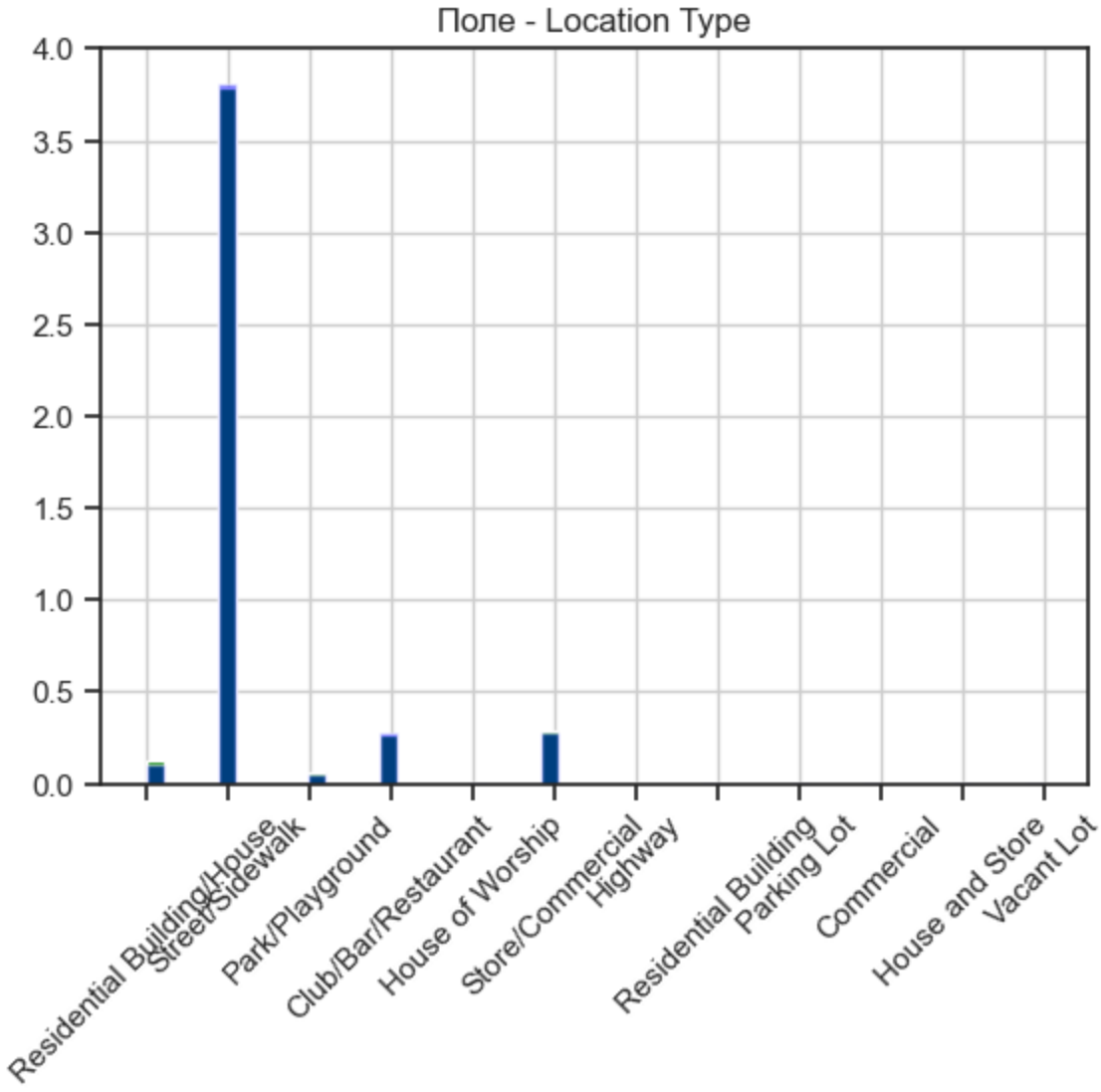
In [12]:

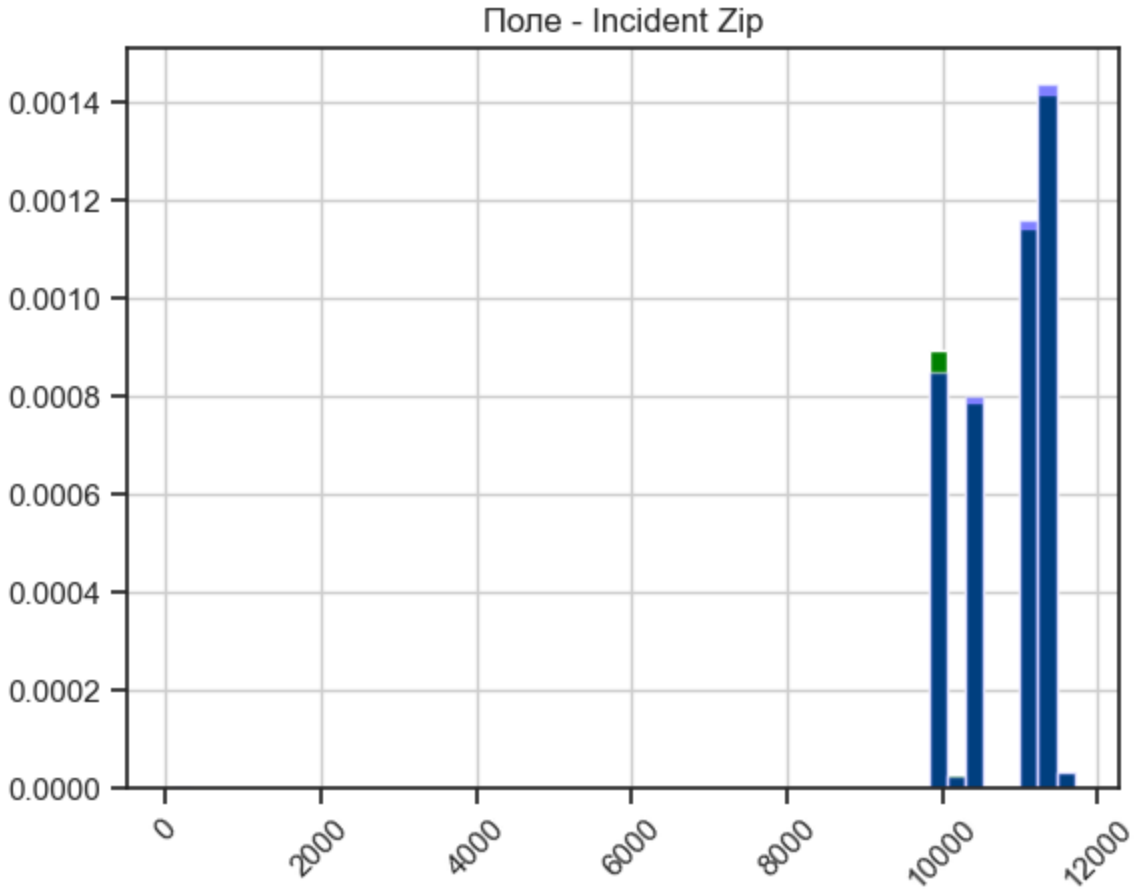
```
plot_hist_diff(dataset, data_drop, rows_to_drop)
```

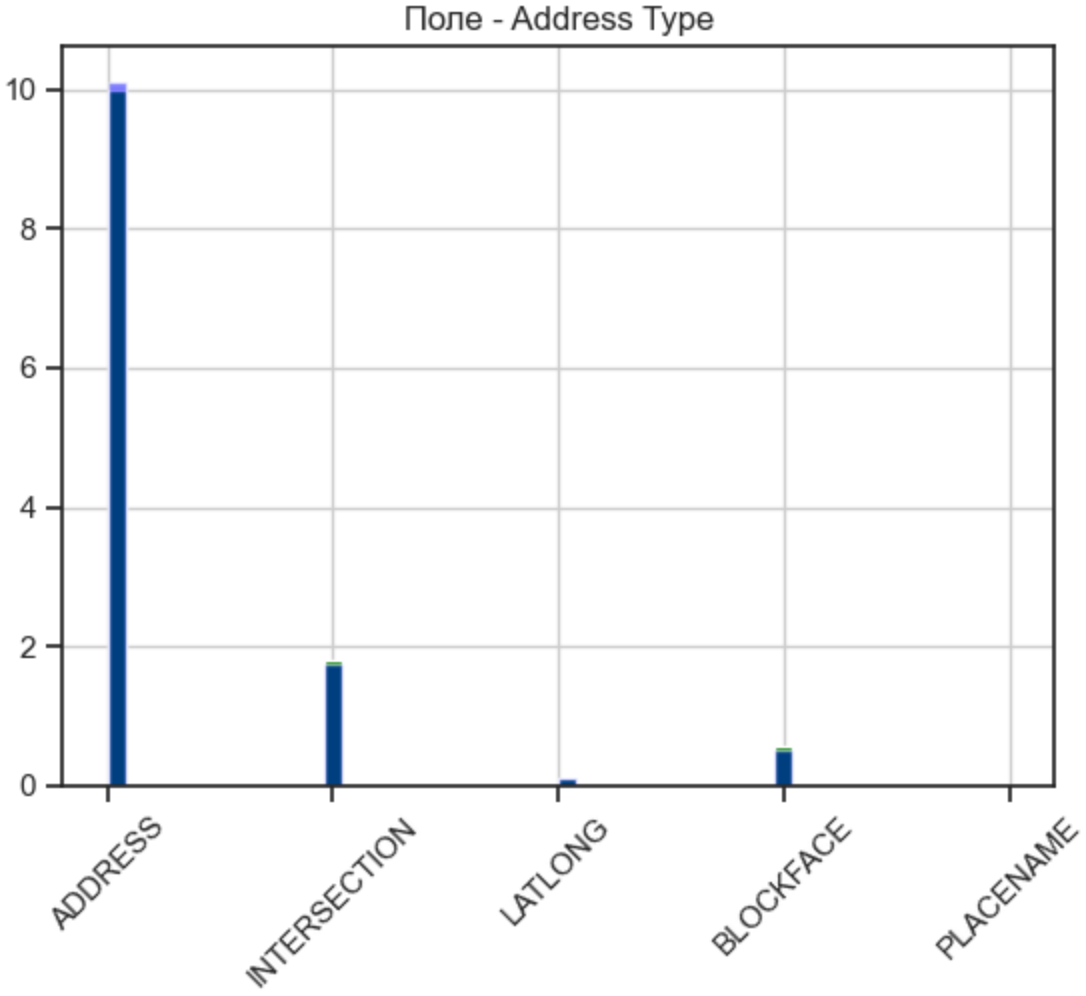
```
C:\Users\User\AppData\Local\Temp\ipykernel_5036\2474487185.py:39: UserWarning: FixedFormat
ter should only be used together with FixedLocator
  ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
```

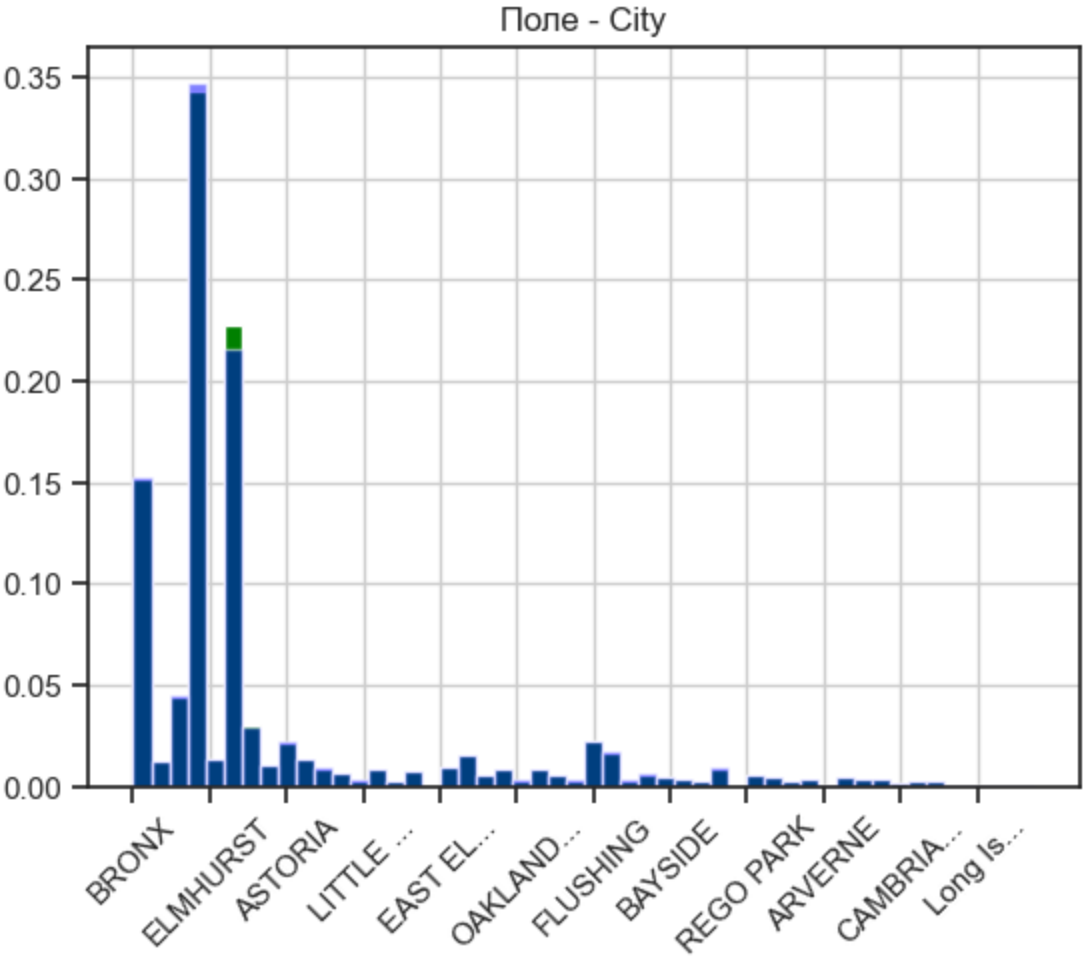

Поле - Closed Date
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
07/06/2...
06/07/2...
11/01/2...
05/23/2...
04/16/2...
09/12/2...
11/02/2...
10/28/2...
04/08/2...
04/19/2...
09/05/2...
04/08/2...
04/08/2...

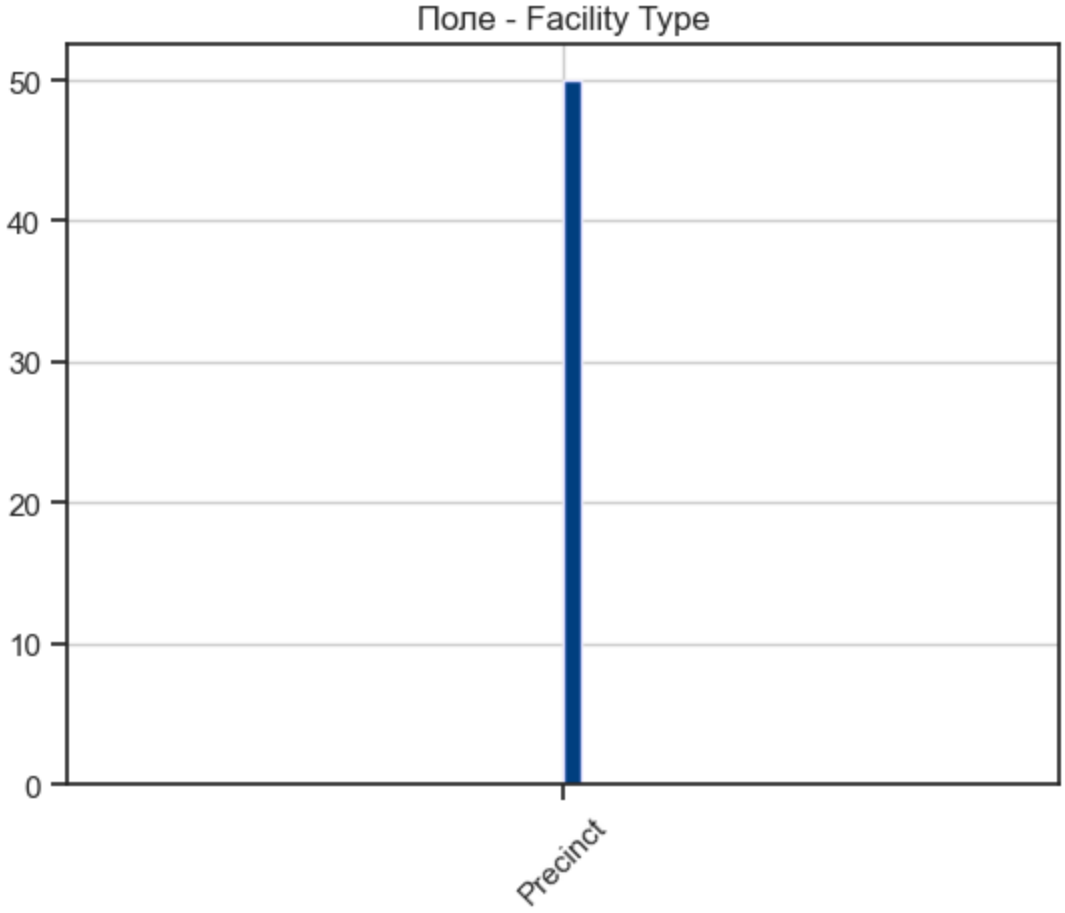

Поле - Descriptor
0.25
0.20
0.15
0.10
0.05
0.00
Other (...
Vehicle
Partial...
With Li...
Car/Tru...
Chained
Engine ...
Double ...
Congest...
Loud Te...
In Public
Chronic...
Police ...

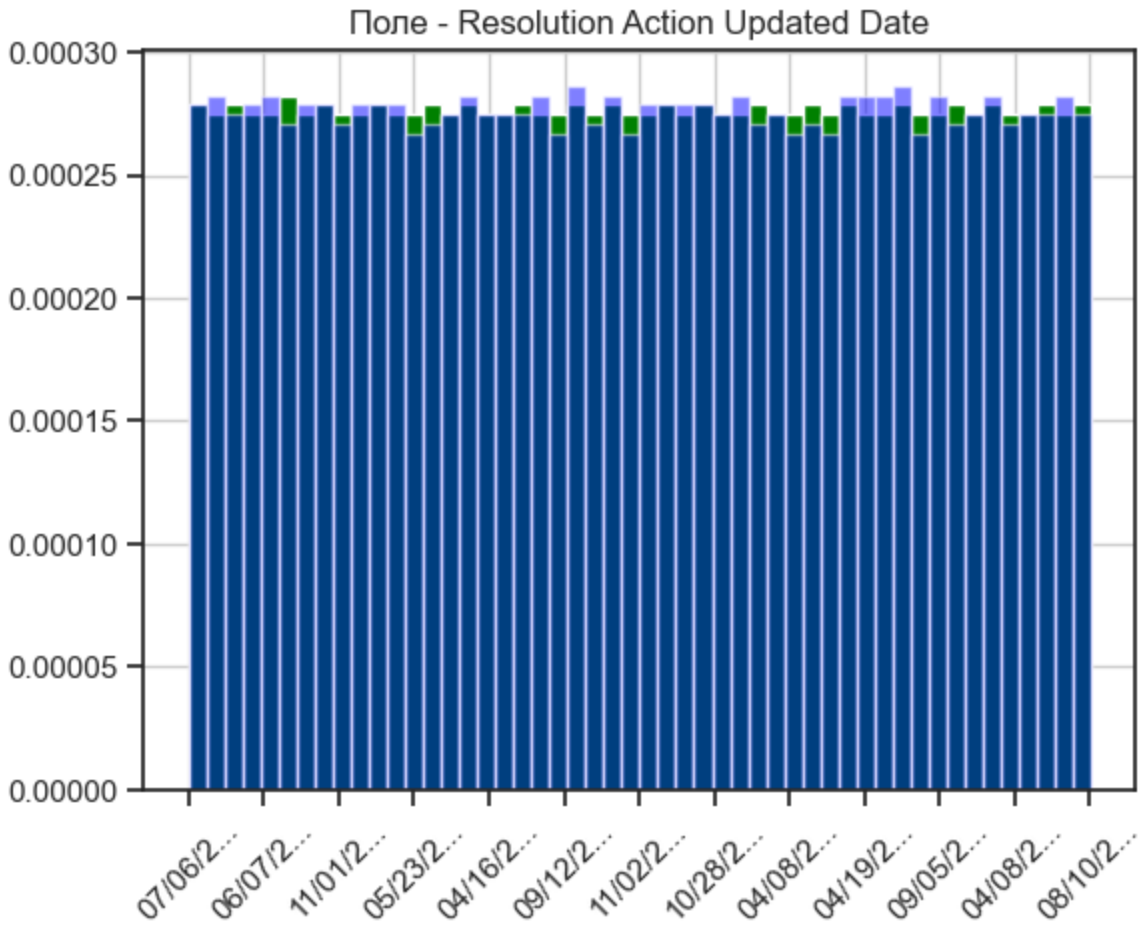

Поле - Location Type
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Residential Building/House
Street/Sidewalk
Park/Playground
Club/Bar/Restaurant
House of Worship
Store/Commercial
Highway
Residential Building
Parking Lot
Commercial
House and Store
Vacant Lot

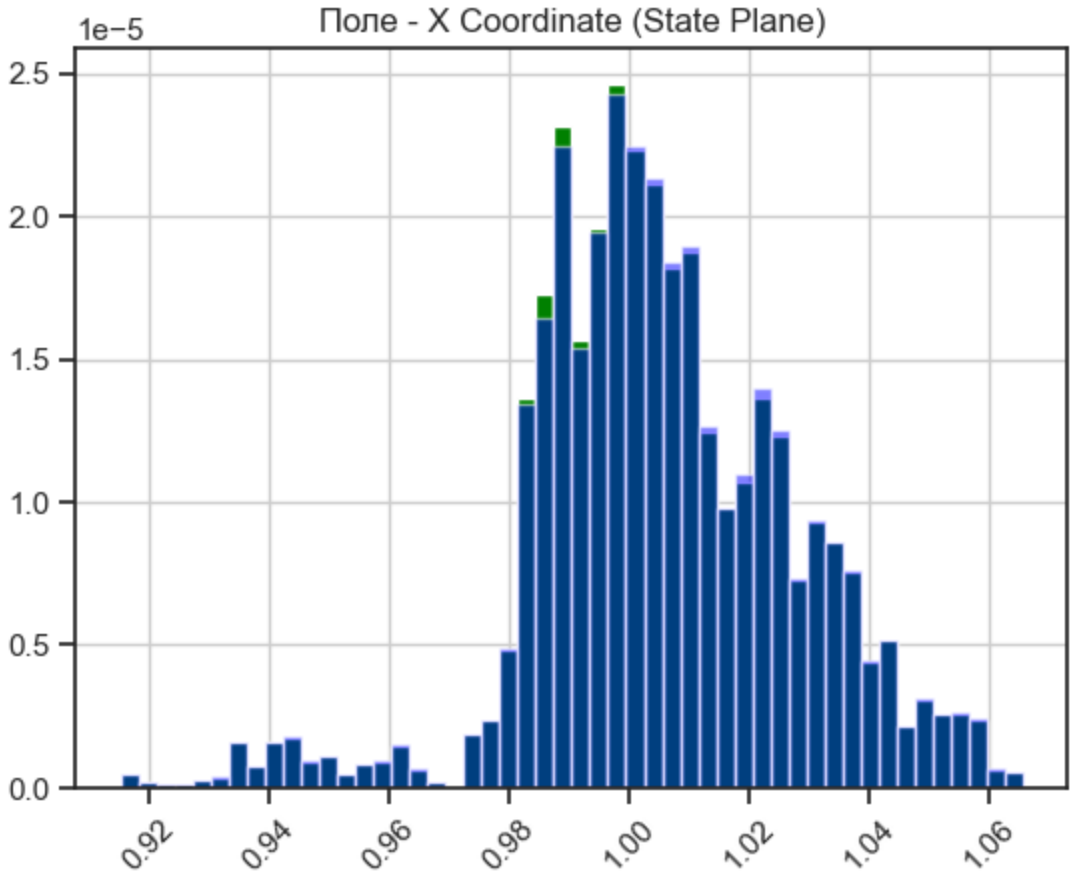

Поле - Incident Zip
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
2000
4000
6000
8000
10000
12000

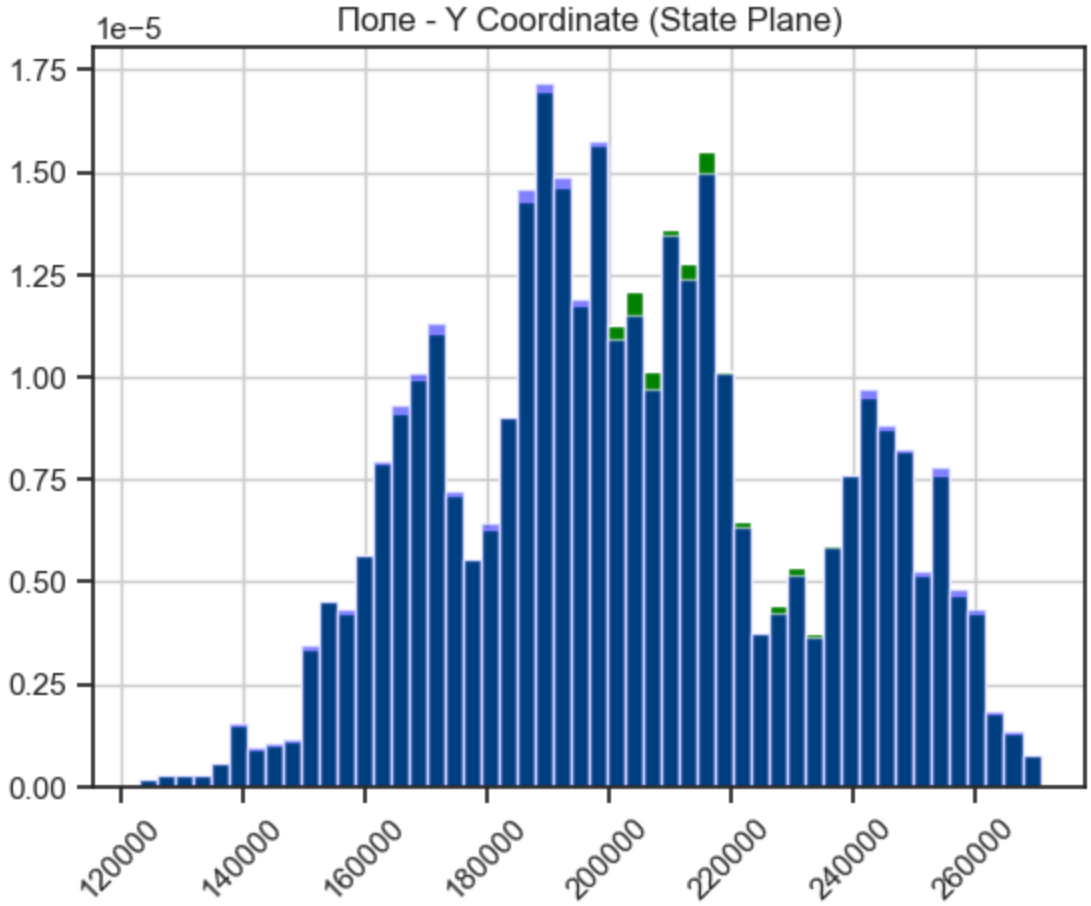

Поле - Address Type
10
8
6
4
2
0
ADDRESS
INTERSECTION
LATLONG
BLOCKFACE
PLACENAME

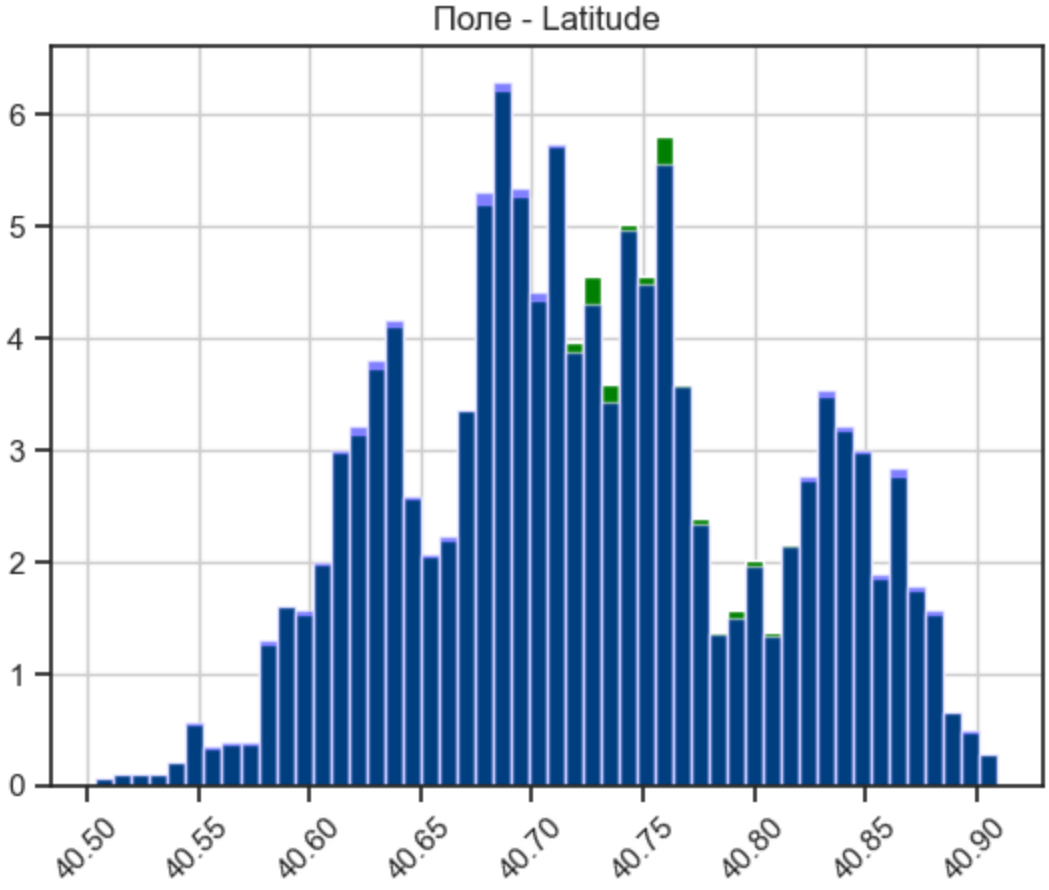

Поле - City
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
BRONX
ELMHURST
ASTORIA
LITTLE ...
EAST EL...
OAKLAND...
FLUSHING
BAYSIDE
REGO PARK
ARVERNE
CAMBRIA...
Long Is...

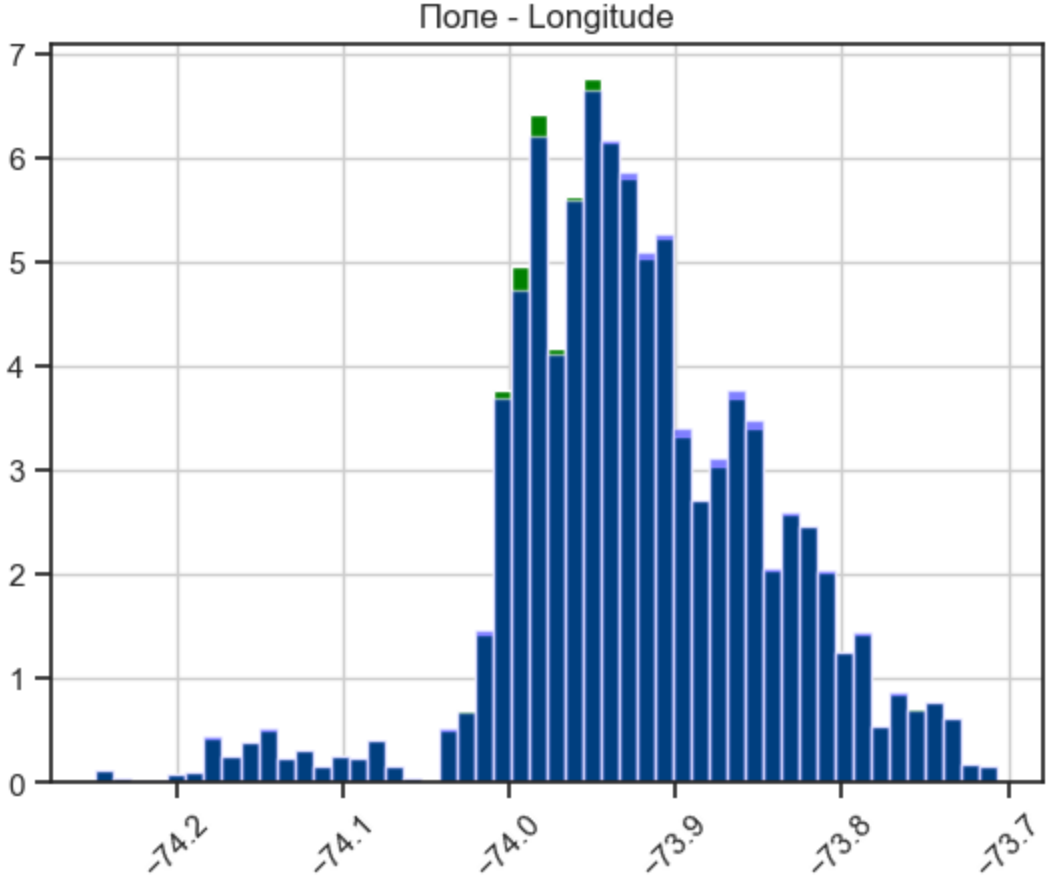

Поле - Facility Type
50
40
30
20
10
0
Precinct

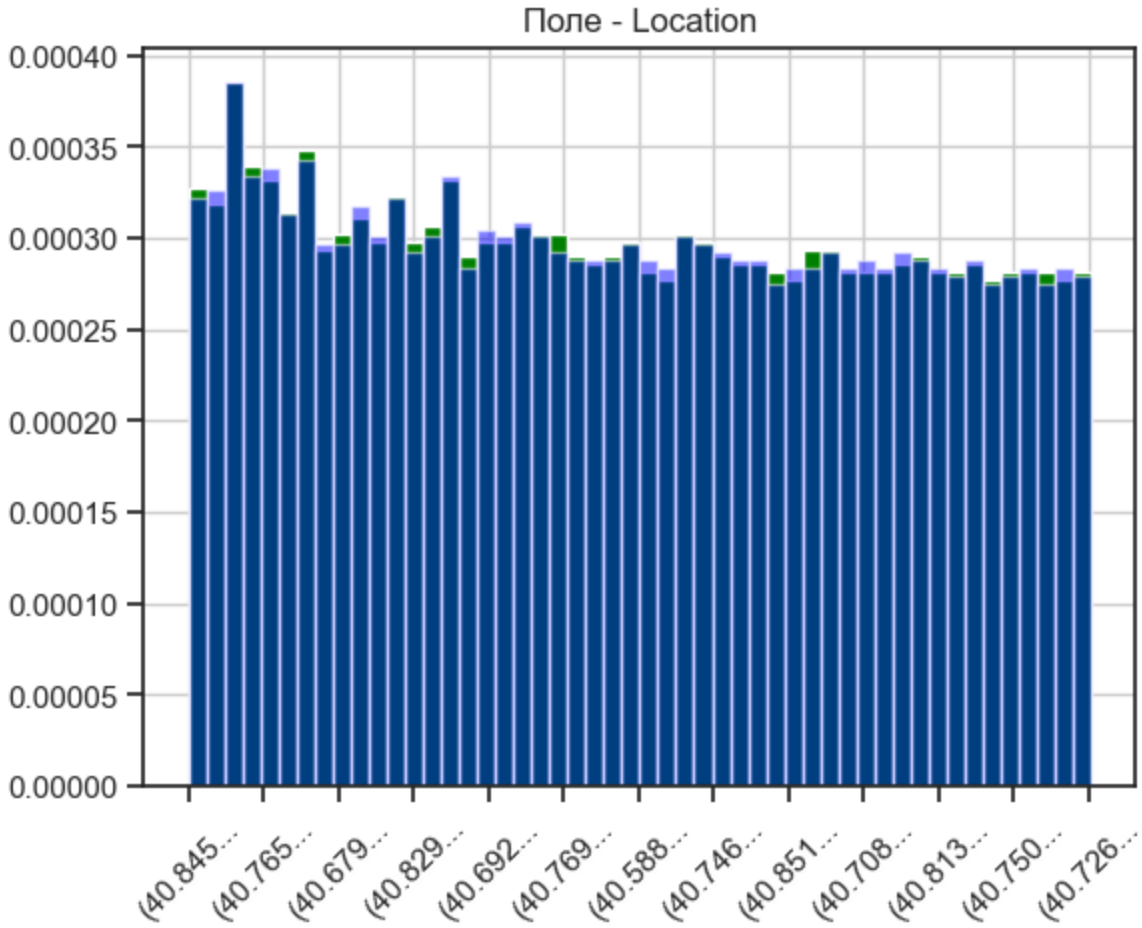

Поле - Resolution Action Updated Date
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
07/06/2...
06/07/2...
11/01/2...
05/23/2...
04/16/2...
09/12/2...
11/02/2...
10/28/2...
04/08/2...
04/19/2...
09/05/2...
04/08/2...
08/10/2...


Поле - X Coordinate (State Plane)
1e−5
2.5
2.0
1.5
1.0
0.5
0.0
0.92
0.94
0.96
0.98
1.00
1.02
1.04
1.06


Поле - Y Coordinate (State Plane)
1e−5
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
120000
140000
160000
180000
200000
220000
240000
260000


Поле - Latitude
0
1
2
3
4
5
6
40.50
40.55
40.60
40.65
40.70
40.75
40.80
40.85
40.90


Поле - Longitude
0
1
2
3
4
5
6
7
−74.2
−74.1
−74.0
−73.9
−73.8
−73.7



Мы удалили строки по тем столбцам, где пропуски составляли небольшой процент (обычно не более 5%) и столбцы там, где пропусков было слишком много (>30%)

In [13]:
```
cols_with_na = [c for c in res.columns if res[c].isnull().sum() > 0]
len(list(zip(res.columns, [i for i in res.dtypes])))
```

Out[13]:
```
39
```

In [14]:
```
[(c, res[c].isnull().mean()) for c in cols_with_na]
```

Out[14]:
```
[('Incident Address', 0.14143709173530247),
 ('Street Name', 0.14143709173530247),
 ('Cross Street 1', 0.1499573984663448),
 ('Cross Street 2', 0.1499573984663448)]
```

Все пропущенные данные пренадлежат категориальным признакам

In [15]:
```
cols_with_na = [c for c in res.columns if res[c].isnull().sum() > 0]
cols_with_na
```

Out[15]:
```
['Incident Address', 'Street Name', 'Cross Street 1', 'Cross Street 2']
```

In [16]:
```
def impute_most_frequent(df, cols_with_na):
    for col in cols_with_na:
        most_frequent_value = df[col].mode()[0]
        df[col].fillna(most_frequent_value, inplace=True)
    return df
```

In [17]:
```
res_new = res[cols_with_na].copy()
```

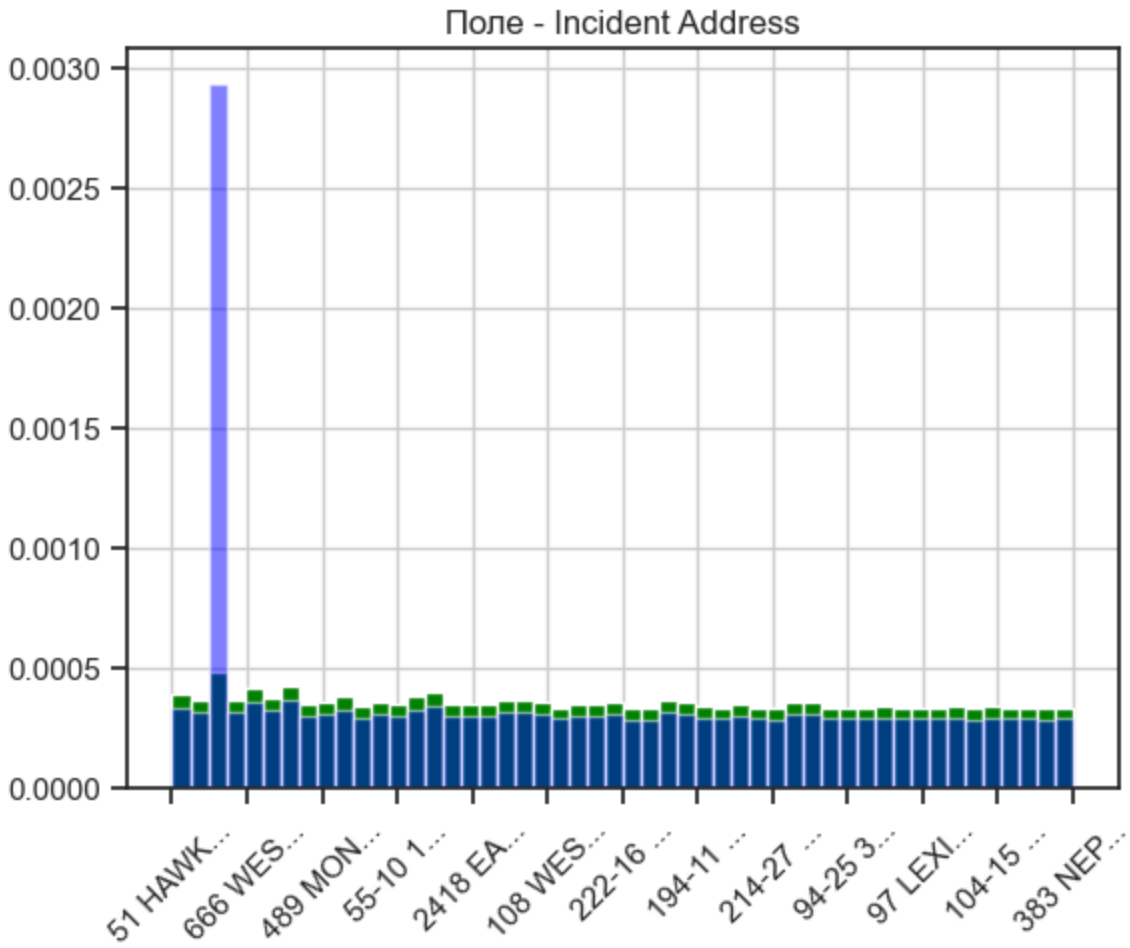
```
[(c, res_new[c].isnull().mean()) for c in cols_with_na]
```

Out[17]:
```
[('Incident Address', 0.14143709173530247),
 ('Street Name', 0.14143709173530247),
 ('Cross Street 1', 0.1499573984663448),
 ('Cross Street 2', 0.1499573984663448)]
```

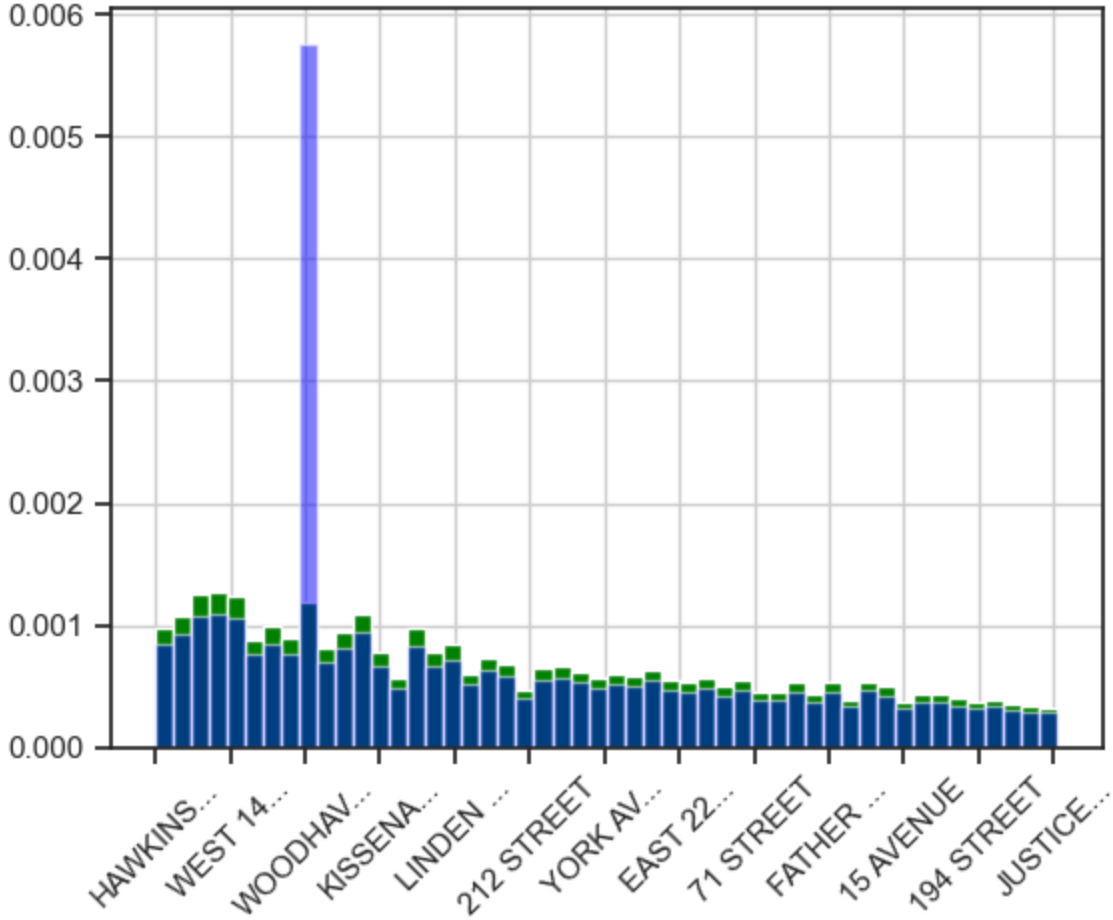
In [18]:
```
res_new = impute_most_frequent(res_new, cols_with_na)
[(c, res_new[c].isnull().mean()) for c in cols_with_na]
```

Out[18]:
```
[('Incident Address', 0.0),
 ('Street Name', 0.0),
 ('Cross Street 1', 0.0),
 ('Cross Street 2', 0.0)]
```

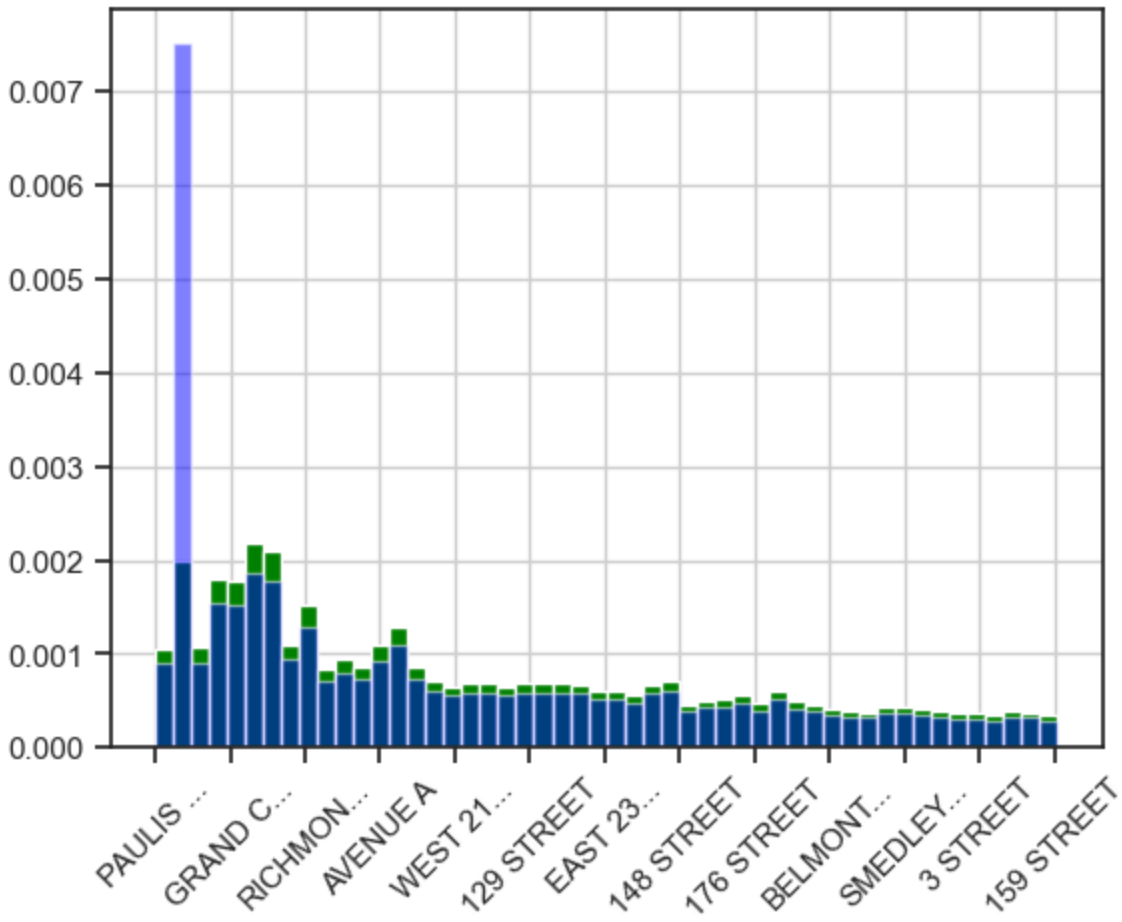
In [19]:
```
plot_hist_diff(res, res_new, cols_with_na)
```

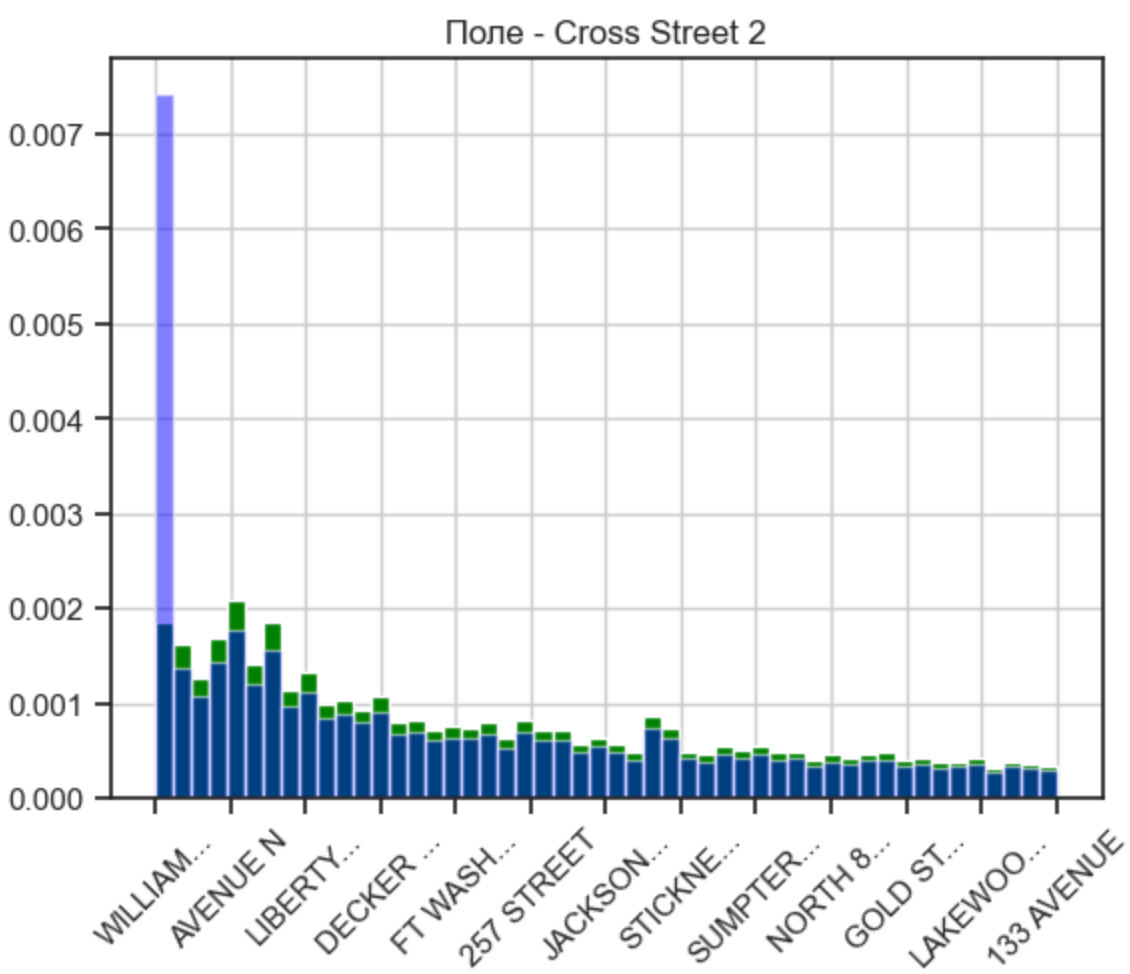


Поле - Street Name



Поле - Cross Street 1



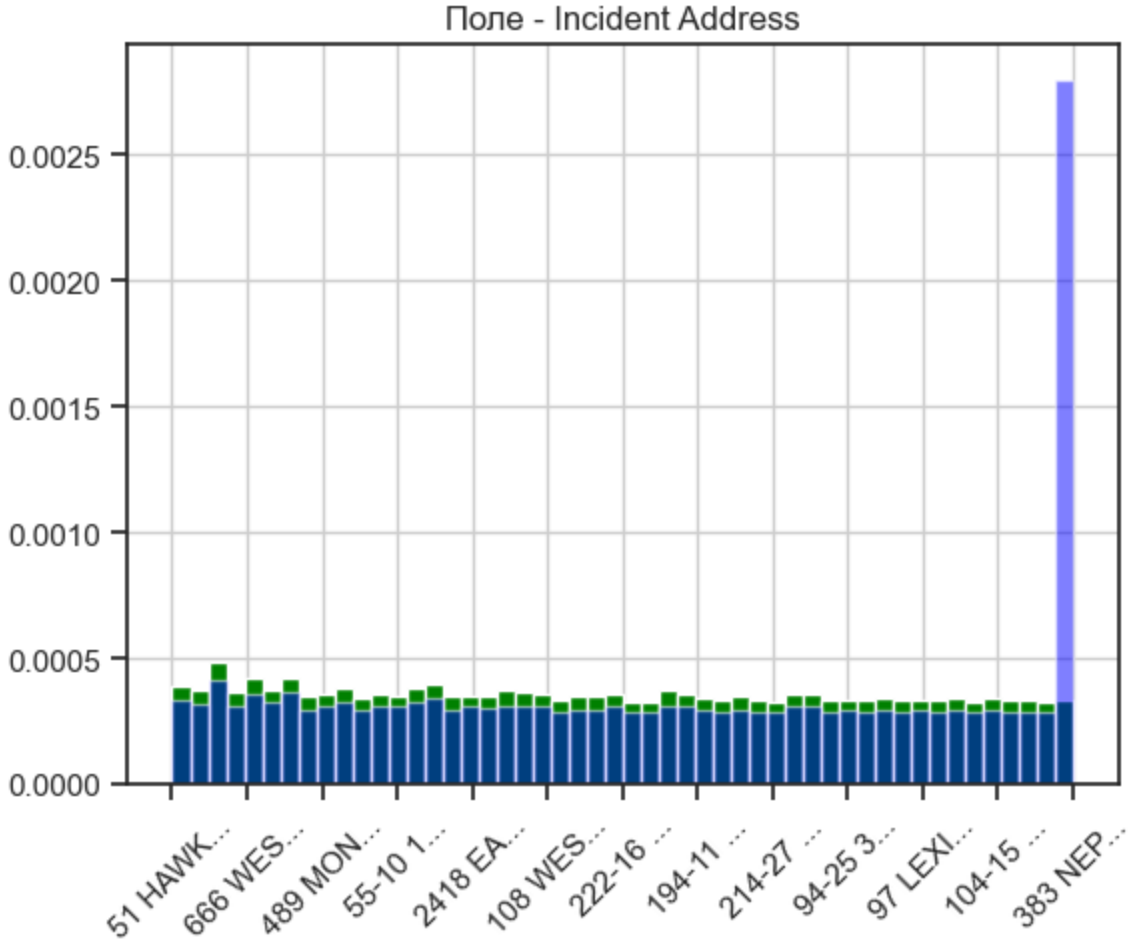


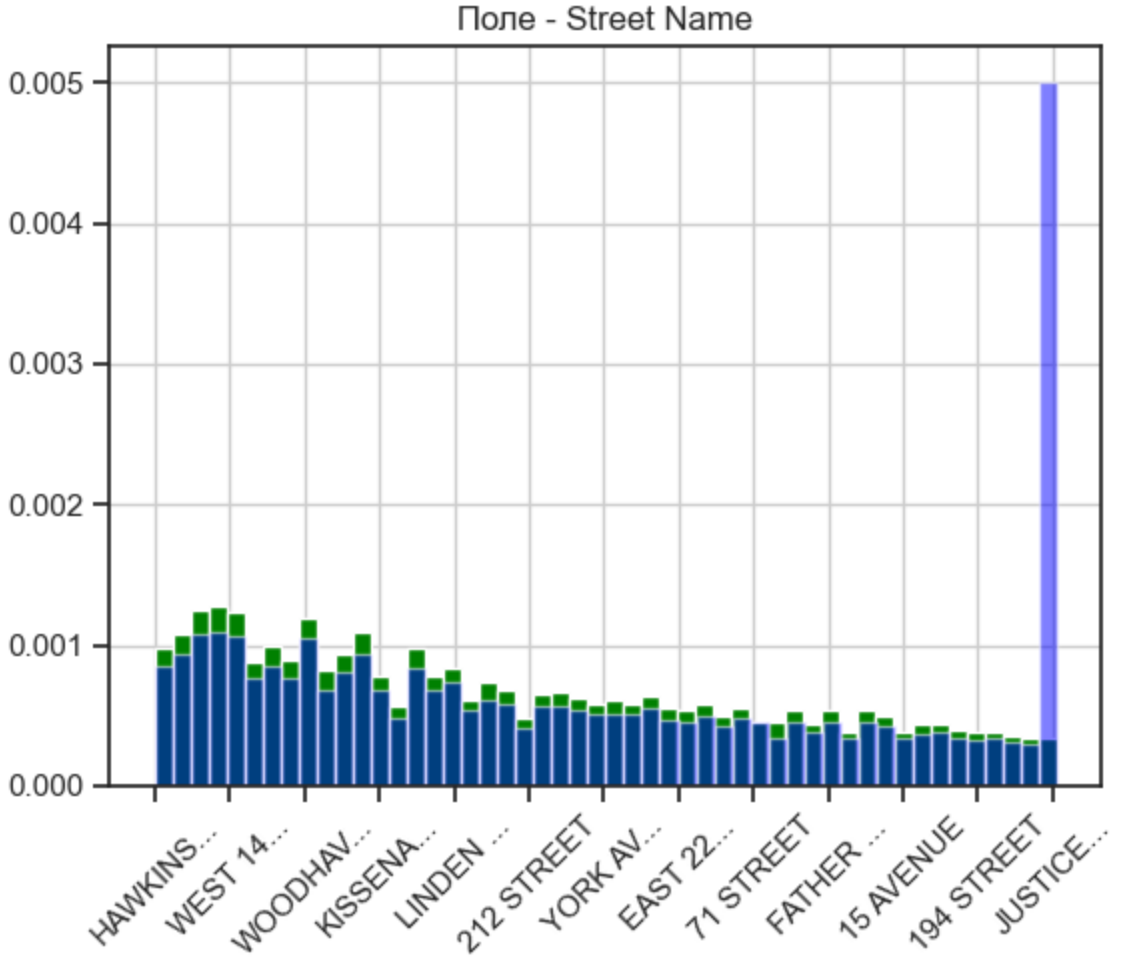
Видим, что заполнение наиболее разпространенным значением существенно меняет распрделение данных.

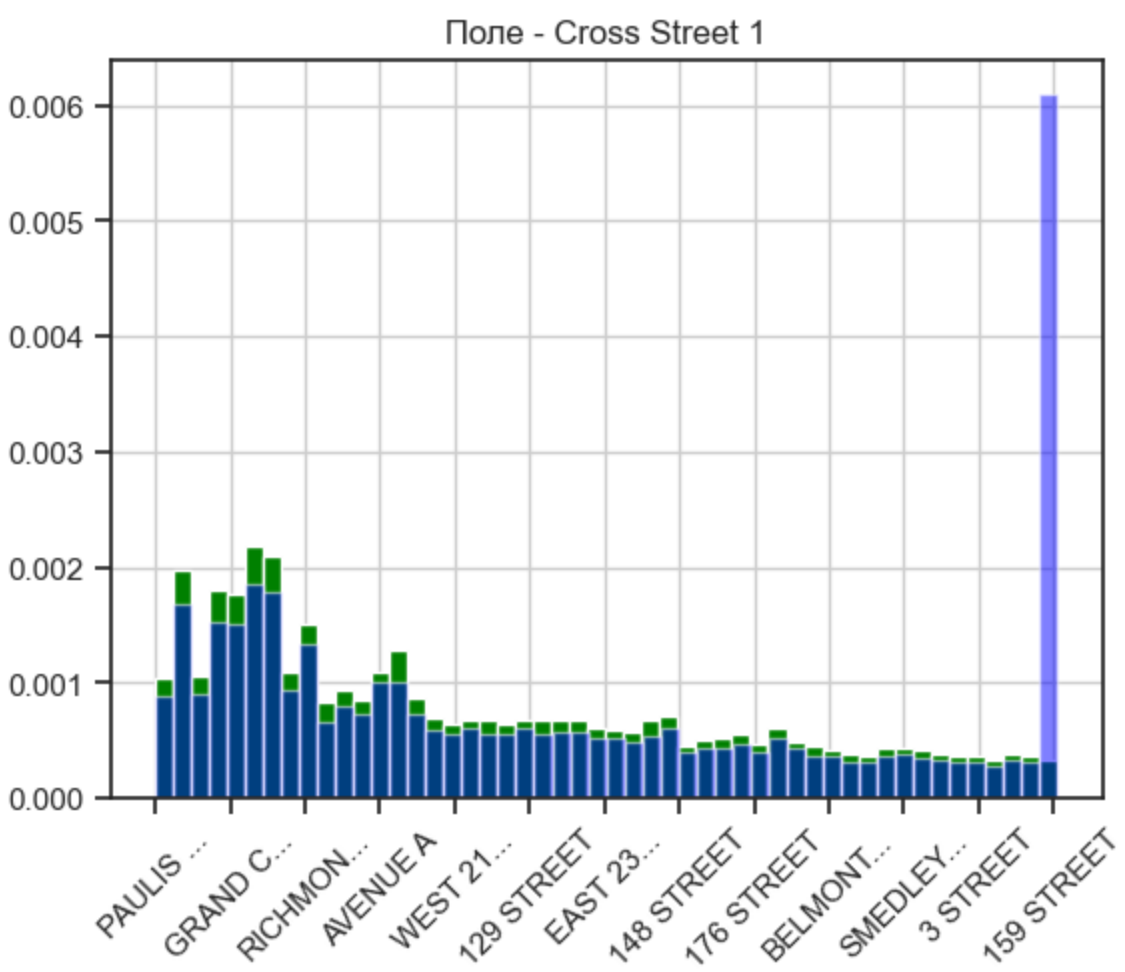
In [20]:
```
res_new = res[cols_to_impute].copy()
```

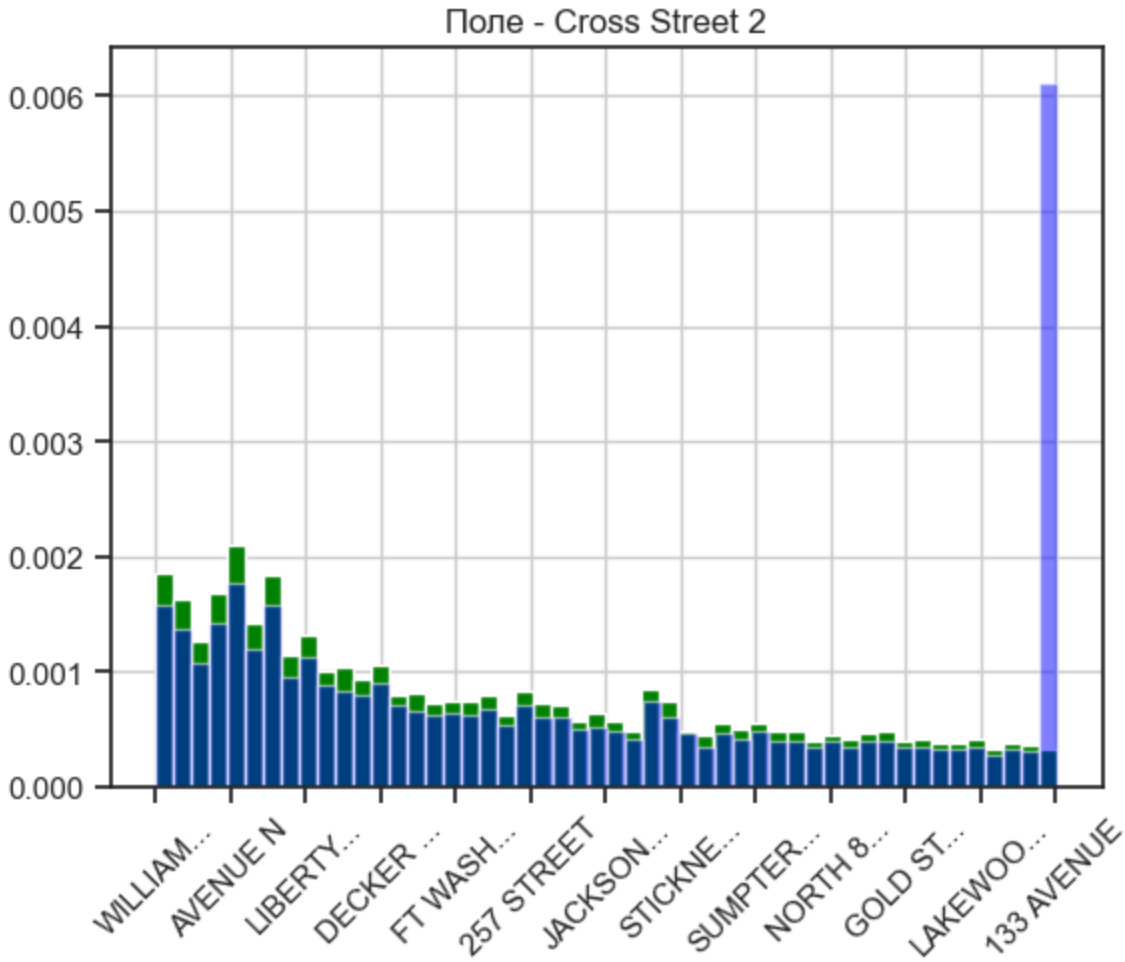
In [21]:
```
res_new['Street Name'].fillna('Unknown Street', inplace =True)
res_new['Cross Street 1'].fillna('Unknown Street', inplace =True)
res_new['Cross Street 2'].fillna('Unknown Street', inplace =True)
res_new['Incident Address'].fillna('Unknown Address', inplace =True)
```

In [22]:
```
plot_hist_diff(res, res_new, cols_to_impute)
```


Поле - Incident Address
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
51 HAWK...
666 WES...
489 MON...
55-10 1...
2418 EA...
108 WES...
222-16 ...
194-11 ...
214-27 ...
94-25 3...
97 LEXI...
104-15 ...
383 NEP...


Поле - Street Name
0.005
0.004
0.003
0.002
0.001
0.000
HAWKINS...
WEST 14...
WOODHAV...
KISSENA...
LINDEN ...
212 STREET
YORK AV...
EAST 22...
71 STREET
FATHER ...
15 AVENUE
194 STREET
JUSTICE...





In [23]:

```
res['Street Name'].fillna('Unknown Street', inplace =True)
res['Cross Street 1'].fillna('Unknown Street', inplace =True)
```

```
res['Cross Street 2'].fillna('Unknown Street', inplace =True)
res['Incident Address'].fillna('Unknown Address', inplace =True)
```

Теперь необходимо произвести кодирование категориальных признаков

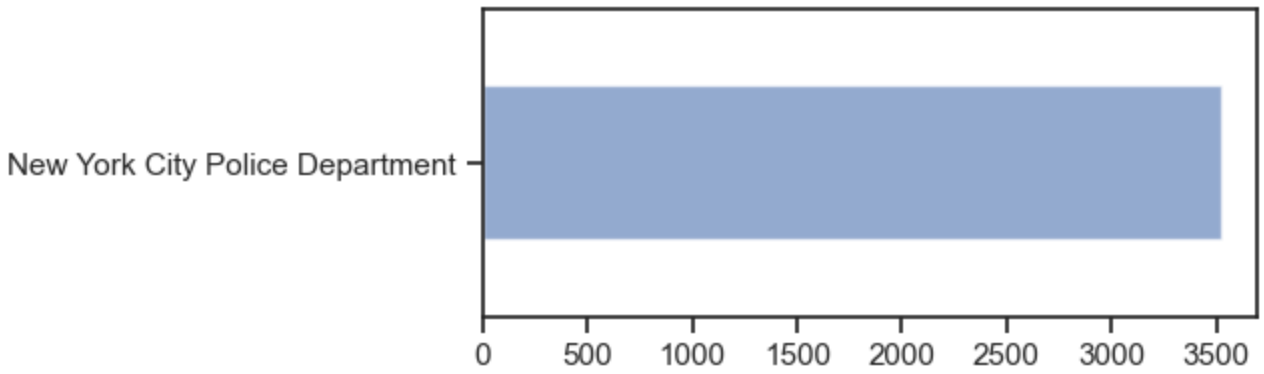
In [24]:
```
# # для начала удалим колонки с пустыми значениями не обнаруженные ранее
# cols_with_na = [c for c in res.columns if res[c].isnull().sum() > 0]
# cols_with_na
# thresh = 0.3
# na_values = ['Unspecified', 'N']

# cols_to_drop = []
# for col in res.columns:
#     na_count = res[col].isin(na_values).sum()
#     if na_count / len(res) > thresh:
#         cols_to_drop.append(col)

# res.drop(cols_to_drop, axis=1, inplace=True)
```

In [39]:
```
list(zip(res.columns, [i for i in res.dtypes]))
```

Out[39]:
```
[('Unique Key', dtype('int64')),
 ('Created Date', dtype('O')),
 ('Closed Date', dtype('O')),
 ('Agency', dtype('O')),
 ('Agency Name', dtype('O')),
 ('Complaint Type', dtype('O')),
 ('Descriptor', dtype('O')),
 ('Location Type', dtype('O')),
 ('Incident Zip', dtype('float64')),
 ('Incident Address', dtype('O')),
 ('Street Name', dtype('O')),
 ('Cross Street 1', dtype('O')),
 ('Cross Street 2', dtype('O')),
 ('Intersection Street 1', dtype('O')),
 ('Intersection Street 2', dtype('O')),
 ('Address Type', dtype('O')),
 ('City', dtype('O')),
 ('Landmark', dtype('O')),
 ('Facility Type', dtype('O')),
 ('Status', dtype('O')),
 ('Due Date', dtype('O')),
 ('Resolution Description', dtype('O')),
 ('Resolution Action Updated Date', dtype('O')),
 ('Community Board', dtype('O')),
 ('Borough', dtype('O')),
 ('X Coordinate (State Plane)', dtype('float64')),
 ('Y Coordinate (State Plane)', dtype('float64')),
 ('Park Borough', dtype('O')),
 ('School or Citywide Complaint', dtype('float64')),
 ('Vehicle Type', dtype('float64')),
 ('Taxi Company Borough', dtype('float64')),
 ('Taxi Pick Up Location', dtype('float64')),
 ('Bridge Highway Name', dtype('O')),
 ('Bridge Highway Direction', dtype('O')),
 ('Road Ramp', dtype('O')),
 ('Bridge Highway Segment', dtype('O')),
 ('Garage Lot Name', dtype('float64')),
 ('Ferry Direction', dtype('O')),
 ('Ferry Terminal Name', dtype('O')),
 ('Latitude', dtype('float64')),
 ('Longitude', dtype('float64')),
 ('Location', dtype('O'))]
```

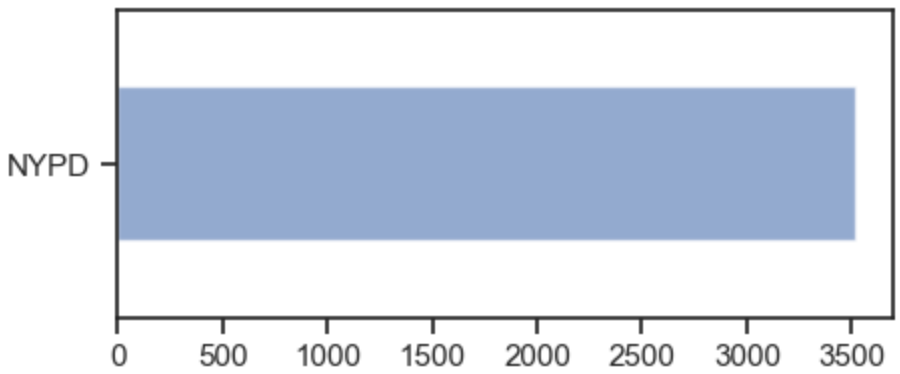
In [49]:
```
res['Agency Name'].value_counts().plot(kind='barh',alpha=0.6,figsize=(5,2))
```

Out[49]:
```
<Axes: >
```



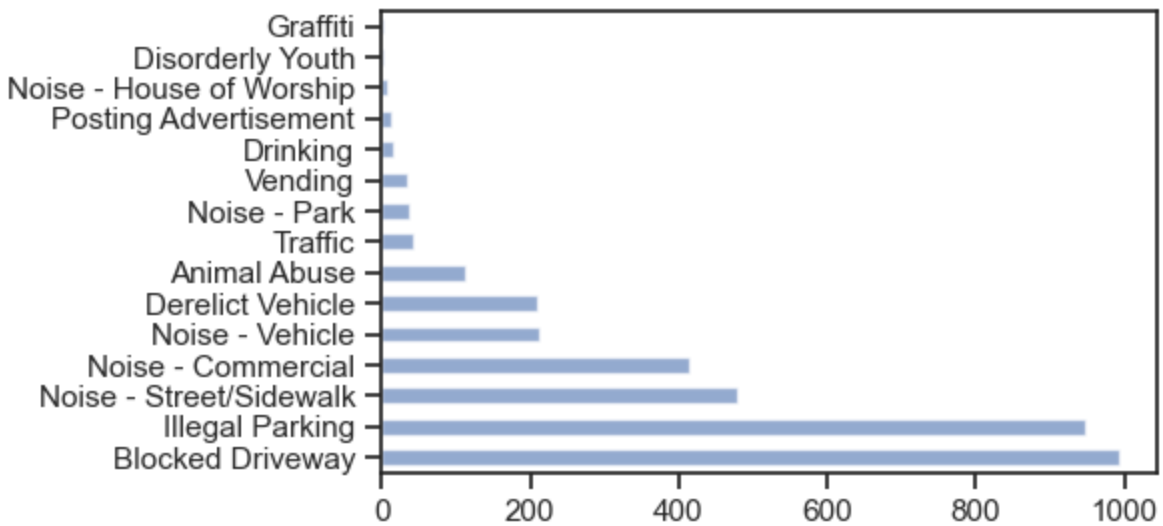
In [50]:
```
res['Agency'].value_counts().plot(kind='barh',alpha=0.6,figsize=(5,2))
```

Out[50]:
```
<Axes: >
```



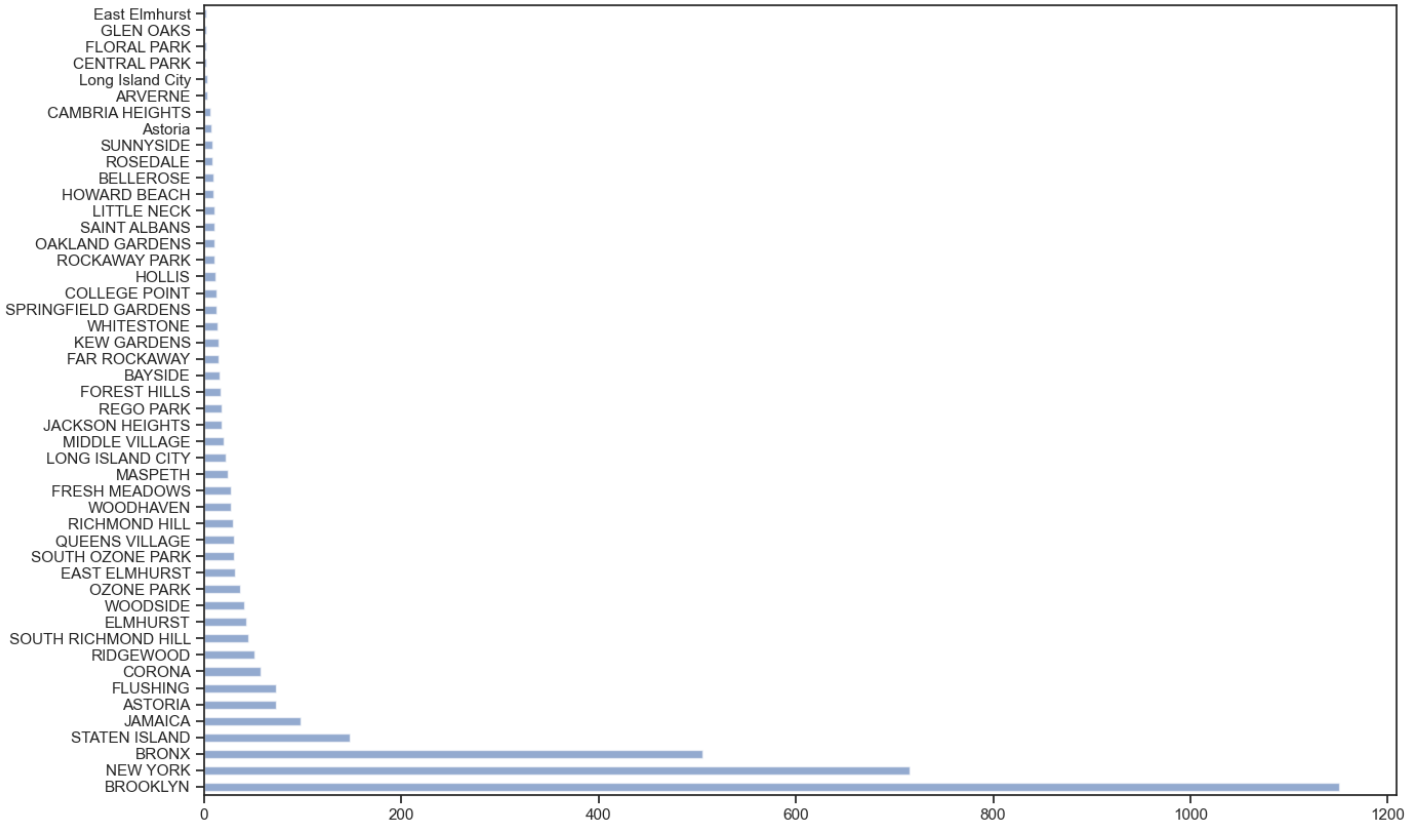
In [52]:
```
res['Complaint Type'].value_counts().plot(kind='barh',alpha=0.6,figsize=(5,3))
```

Out[52]:
```
<Axes: >
```



In [58]:
```
res['City'].value_counts().plot(kind='barh',alpha=0.6,figsize=(15,10))
```

Out[58]:
```
<Axes: >
```



In [72]:
```
# отберем колонки с признаками для кодирования
cols_to_code = ['Created Date','Closed Date',
                'Complaint Type','City','Latitude','Longitude']
```

In [105…
```
res_code = res[cols_to_code]
```

In [106…
```
res_code.head()
```

Out[106…

	Created Date	Closed Date	Complaint Type	City	Latitude	Longitude
192819	07/06/2015 12:16:19 PM	07/06/2015 03:37:28 PM	Animal Abuse	BRONX	40.845878	-73.788856
9654	12/20/2015 11:58:51 PM	12/21/2015 07:41:28 AM	Noise - Street/Sidewalk	BRONX	40.868207	-73.864362
77616	10/16/2015 05:36:58 PM	10/17/2015 06:30:32 AM	Blocked Driveway	WOODSIDE	40.738554	-73.905243
144357	08/18/2015 11:01:53 PM	08/19/2015 01:03:09 AM	Posting Advertisement	STATEN ISLAND	40.549094	-74.173633
280552	04/20/2015 04:43:02 PM	04/21/2015 01:12:45 AM	Illegal Parking	BROOKLYN	40.608238	-73.950145

Даты и координаты - числовые признаки, требующие нормализации. Районы NY и типы жалоб - категориальные признаки, требующие кодирования. Поскольку вероятно, что при обработке данных придется решать задачу определения по координатам района, то кодирование данных о районах должно позволять и обратное декодирование. Используем OneHot.

In [74]:
```
# # !pip install category_encoders
# from category_encoders.target_encoder import TargetEncoder as ce_TargetEncoder
# ce_TargetEncoder1 = ce_TargetEncoder()
```

```
# data_MEAN_ENC = ce_TargetEncoder1.fit_transform(res_code[res_code.columns.difference(['(
```

```
pd.get_dummies(res_code[['Complaint Type']]).head()
```

Out[74]:

	Complaint Type_Animal Abuse	Complaint Type_Blocked Driveway	Complaint Type_Derelict Vehicle	Complaint Type_Disorderly Youth	Complaint Type_Drinking	Complaint Type_Graffiti	Complaint Type_Illegal Parking	Cor Type Com
192819	1	0	0	0	0	0	0	
9654	0	0	0	0	0	0	0	
77616	0	1	0	0	0	0	0	
144357	0	0	0	0	0	0	0	
280552	0	0	0	0	0	0	1	

In [64]:

```
pd.get_dummies(res_code[['City']]).head()
```

Out[64]:

	City_ARVERNE	City_ASTORIA	City_Astoria	City_BAYSIDE	City_BELLEROSE	City_BRONX	City_BROOKLYN	Ci
192819	0	0	0	0	0	1	0	
9654	0	0	0	0	0	1	0	
77616	0	0	0	0	0	0	0	
144357	0	0	0	0	0	0	0	
280552	0	0	0	0	0	0	1	

5 rows × 48 columns

Теперь нормализуем числовые признаки

In [95]:

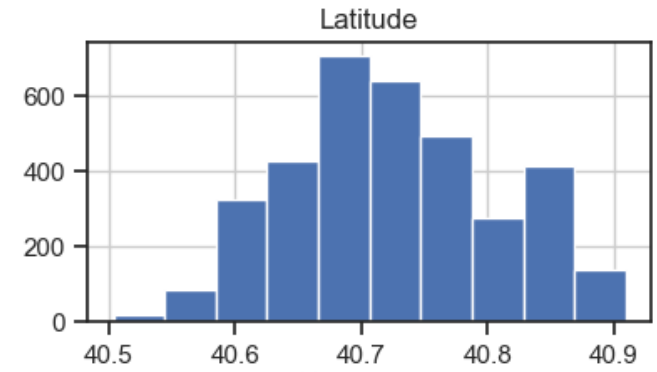
```
import scipy.stats as stats
def diagnostic_plots(df, variable):
    plt.figure(figsize=(15,6))
    # гистограмма
    plt.subplot(1, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(1, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    plt.show()
```

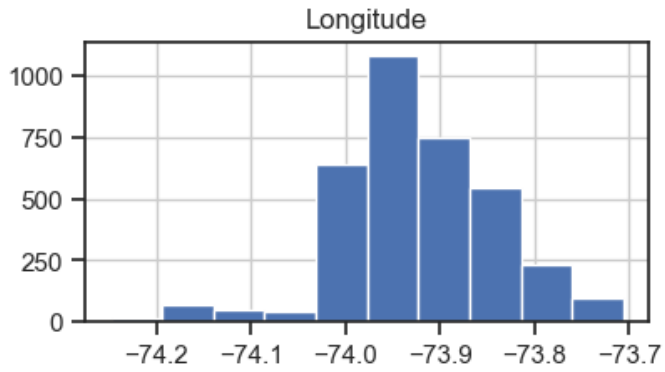
In [102…

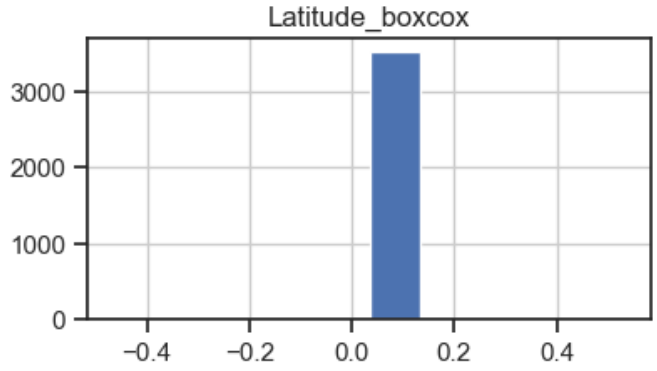
```
res_code.hist(figsize=(10,5))
```

Out[102…

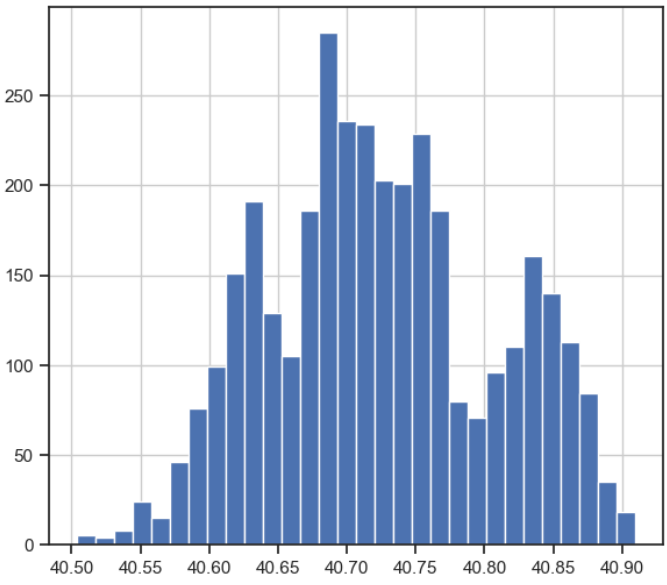
```
array([[<Axes: title={'center': 'Latitude'}>,
        <Axes: title={'center': 'Longitude'}>],
       [<Axes: title={'center': 'Latitude_boxcox'}>, <Axes: >]],
      dtype=object)
```

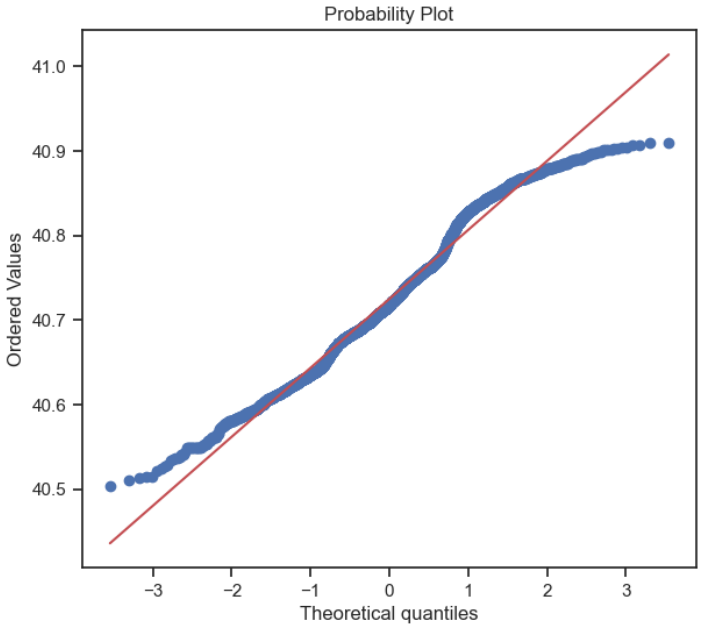






In [82]:
```
diagnostic_plots(res_code,'Latitude')
```

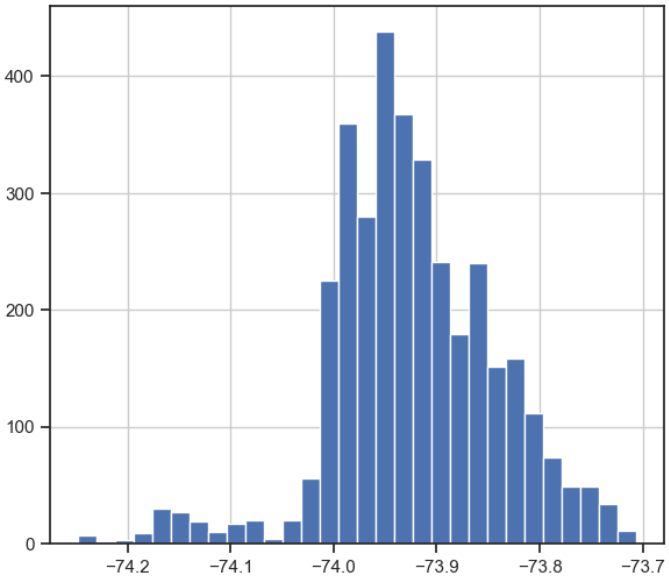


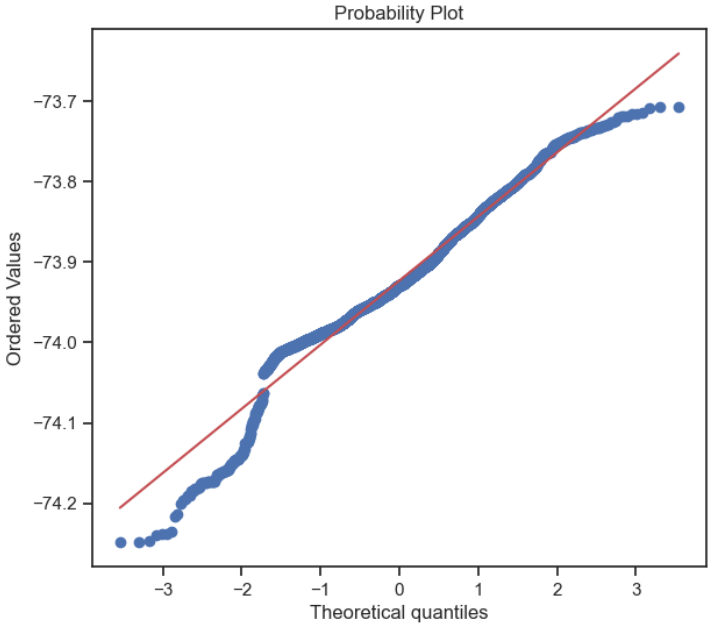


In [111…

Out[111…
```
array([0.03434994, 0.03434994, 0.03434994, ..., 0.03434994, 0.03434994,
       0.03434994])
```

In [83]:
```
diagnostic_plots(res_code,'Longitude')
```


400
300
200
100
0
−74.2
−74.1
−74.0
−73.9
−73.8
−73.7


Probability Plot
Ordered Values
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
−3
−2
−1
0
1
2
3
Theoretical quantiles