Рубежный контроль №1

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Вариант 15

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")
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
Normalizer
```

In [2]:

```
df = pd.read_csv('rest.csv')
```

Получим общую информацию о датасете.

In [3]:

```
df.head()
```

Out[3]:

	business_id	business_name	business_address	business_city	business_state	business_postal_code	business_latitude	business_longitude	business_location	business_phone_number	inspection_type	violation_id	violation_description	risk_category	Neighborhoods (old)	Police Districts	Supervisor Districts	Fire Prevention Districts	Zip Codes	Analysis Neighborhoods

10192	Cochinita #2	2 Marina Blvd Fort Mason	San Francisco	CA	NaN	NaN	NaN	NaN	1.415043e+10	New Ownership	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
97975	BREADBELLY	1408 Clement St	San Francisco	CA	94118	NaN	NaN	NaN	1.415724e+10	Routine - Unscheduled	97975_20190725_103124	Inadequately cleaned or sanitized food contact...	Moderate Risk	NaN	NaN	NaN	NaN	NaN	NaN
92982	Great Gold Restaurant	3161 24th St.	San Francisco	CA	94110	NaN	NaN	NaN	NaN	New Ownership	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
101389	HOMAGE	214 CALIFORNIA ST	San Francisco	CA	94111	NaN	NaN	NaN	1.415488e+10	New Construction	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
85986	Pronto Pizza	798 Eddy St	San Francisco	CA	94109	NaN	NaN	NaN	NaN	New Ownership	85986_20161011_103114	High risk vermin infestation	High Risk	NaN	NaN	NaN	NaN	NaN	NaN

5 rows × 23 columns

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53973 entries, 0 to 53972
Data columns (total 23 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   business_id                 53973 non-null  int64  
 1   business_name               53973 non-null  object 
 2   business_address            53973 non-null  object 
 3   business_city               53973 non-null  object 
 4   business_state              53973 non-null  object 
 5   business_postal_code        52955 non-null  object 
 6   business_latitude           34417 non-null  float64
 7   business_longitude          34417 non-null  float64
 8   business_location           34417 non-null  object 
 9   business_phone_number       17035 non-null  float64
 10  inspection_id               53973 non-null  object 
 11  inspection_date             53973 non-null  object 
 12  inspection_score            40363 non-null  float64
 13  inspection_type             53973 non-null  object 
 14  violation_id                41103 non-null  object 
 15  violation_description       41103 non-null  object 
 16  risk_category               41103 non-null  object 
 17  Neighborhoods (old)         34379 non-null  float64
 18  Police Districts            34379 non-null  float64
 19  Supervisor Districts        34379 non-null  float64
 20  Fire Prevention Districts   34327 non-null  float64
 21  Zip Codes                   34397 non-null  float64
 22  Analysis Neighborhoods      34379 non-null  float64
dtypes: float64(10), int64(1), object(12)
memory usage: 9.5+ MB
```

In [5]:

```
def draw_missing(df):
    total = df.isnull().sum().sort_values(ascending=False)
    percent = 
(df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)*100
    missing_data = pd.concat([total, percent], axis=1, keys=['Total', 
'Percent'])
    return missing_data
draw_missing(df)
```

Out[5]:

	Total	Percent
business_phone_number	36938	68.437923
Fire Prevention Districts	19646	36.399681
Analysis Neighborhoods	19594	36.303337
Supervisor Districts	19594	36.303337
Police Districts	19594	36.303337
Neighborhoods (old)	19594	36.303337
Zip Codes	19576	36.269987
business_latitude	19556	36.232931
business_longitude	19556	36.232931
business_location	19556	36.232931
inspection_score	13610	25.216312
violation_description	12870	23.845256
risk_category	12870	23.845256
violation_id	12870	23.845256
business_postal_code	1018	1.886128
business_id	0	0.000000
inspection_type	0	0.000000
business_name	0	0.000000
inspection_id	0	0.000000
business_state	0	0.000000
business_city	0	0.000000

business_address	0	0.000000
inspection_date	0	0.000000

Выясним в каких типах данных присутствуют пропуски

In [6]:

```
total_count = df.shape[0]
```

In [7]:

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
num_cols = []
for col in df.columns:
    # Количество пустых значений
    temp_null_count = df[df[col].isnull()].shape[0]
    dt = str(df[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 {},
{}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка business_latitude. Тип данных float64. Количество пустых значений
19556, 36.23%.
Колонка business_longitude. Тип данных float64. Количество пустых значений
19556, 36.23%.
Колонка business_phone_number. Тип данных float64. Количество пустых
значений 36938, 68.44%.
Колонка inspection_score. Тип данных float64. Количество пустых значений
13610, 25.22%.
Колонка Neighborhoods (old). Тип данных float64. Количество пустых
значений 19594, 36.3%.
Колонка Police Districts. Тип данных float64. Количество пустых значений
19594, 36.3%.
Колонка Supervisor Districts. Тип данных float64. Количество пустых
значений 19594, 36.3%.
Колонка Fire Prevention Districts. Тип данных float64. Количество пустых
значений 19646, 36.4%.
Колонка Zip Codes. Тип данных float64. Количество пустых значений 19576,
36.27%.
Колонка Analysis Neighborhoods. Тип данных float64. Количество пустых
значений 19594, 36.3%.
```

In [8]:

```
df_num = df[num_cols]
```

```
df_num
```

Out [8]:

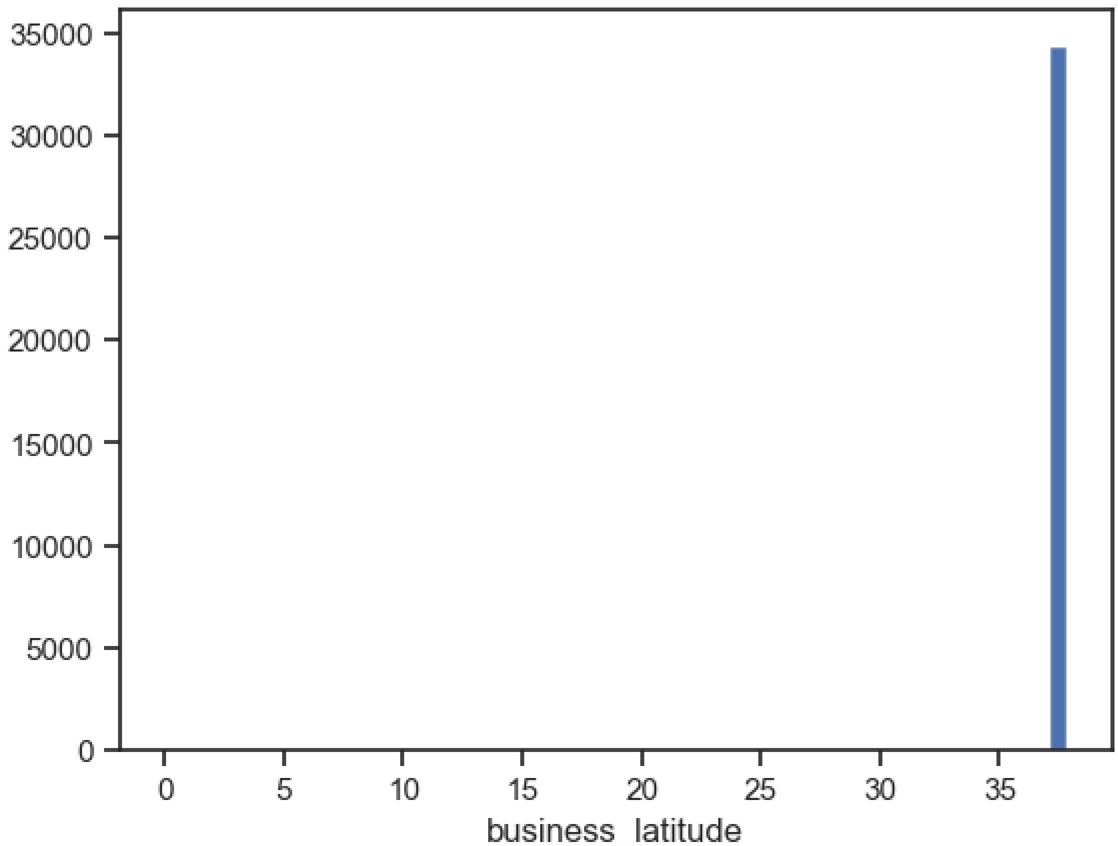
	business_latitude	business_longitude	business_phone_number	inspection_score	Neighborhoods (old)	Police Districts	Supervisor Districts	Fire Prevention Districts	Zip Codes	Analysis Neighborhoods
0	NaN	NaN	1.415043e+10	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	1.415724e+10	96.0	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	1.415488e+10	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...
53968	NaN	NaN	NaN	80.0	NaN	NaN	NaN	NaN	NaN	NaN
53969	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
53970	NaN	NaN	NaN	92.0	NaN	NaN	NaN	NaN	NaN	NaN
53971	NaN	NaN	NaN	76.0	NaN	NaN	NaN	NaN	NaN	NaN
53972	NaN	NaN	NaN	80.0	NaN	NaN	NaN	NaN	NaN	NaN

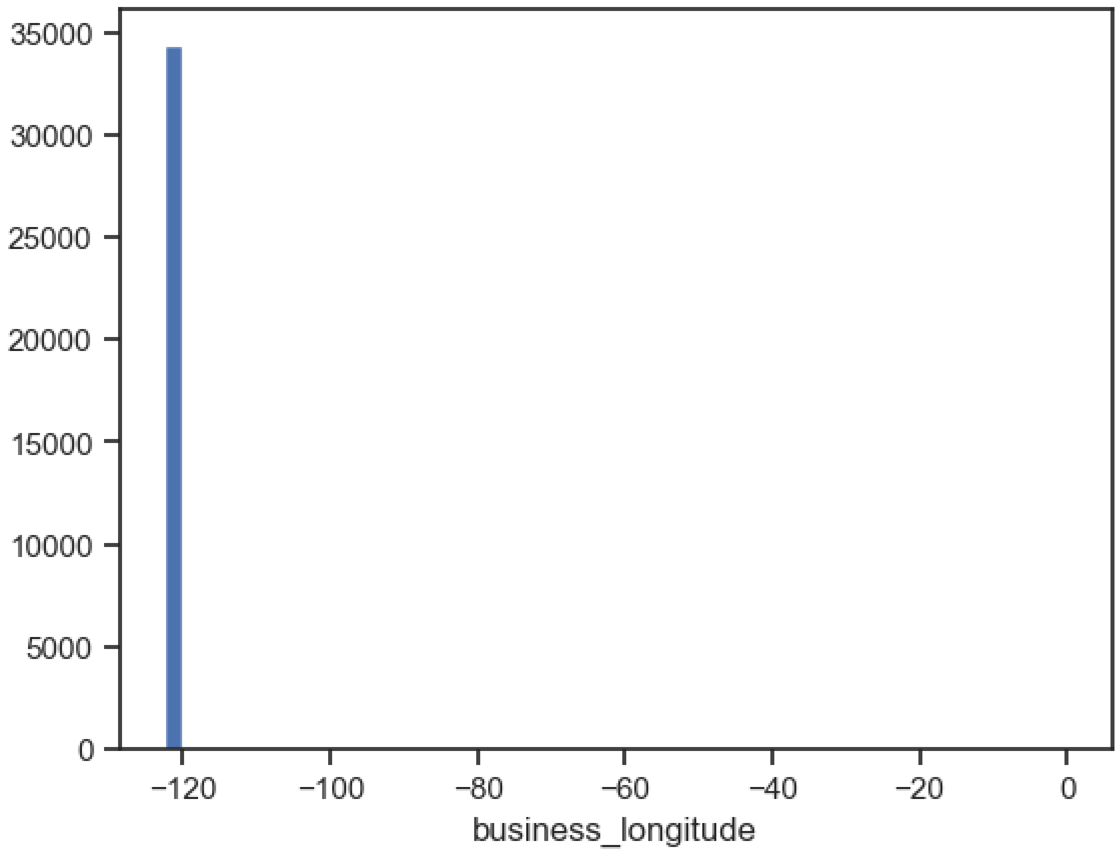
53973 rows × 10 columns

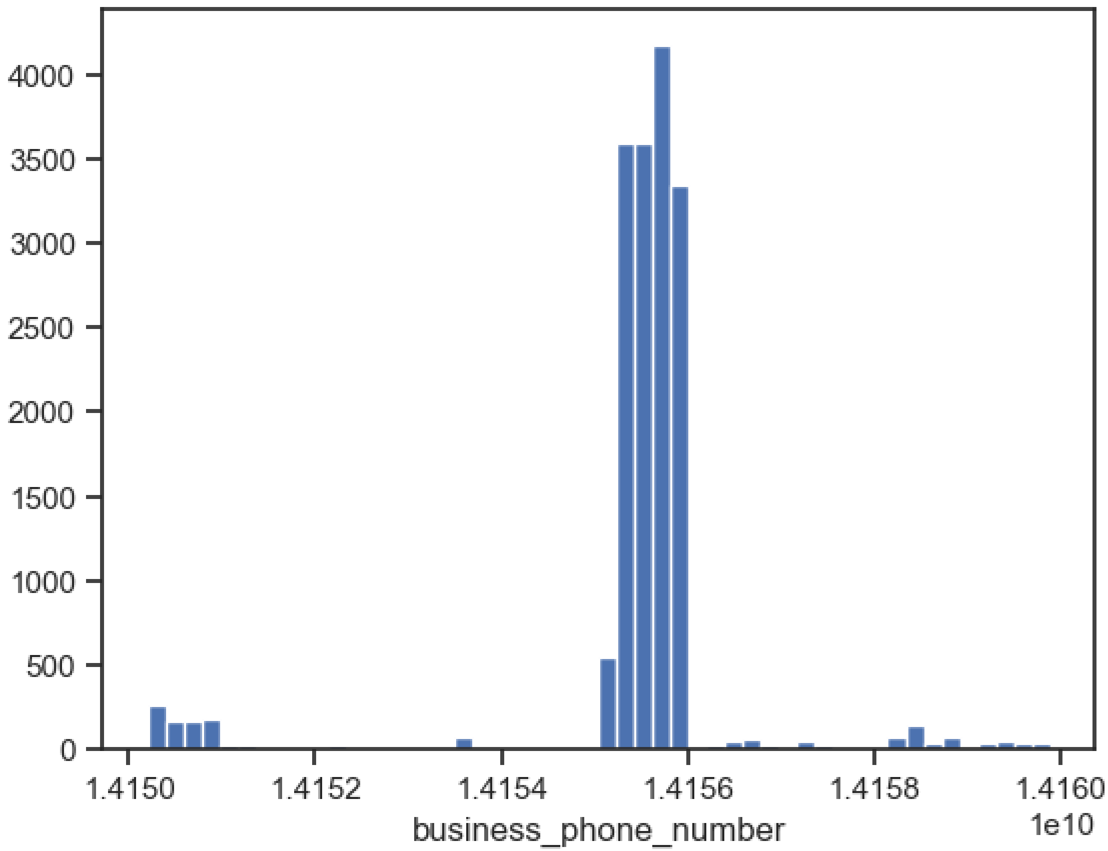
In [9]:

```
for col in df_num:
    plt.hist(df[col], 50)
```

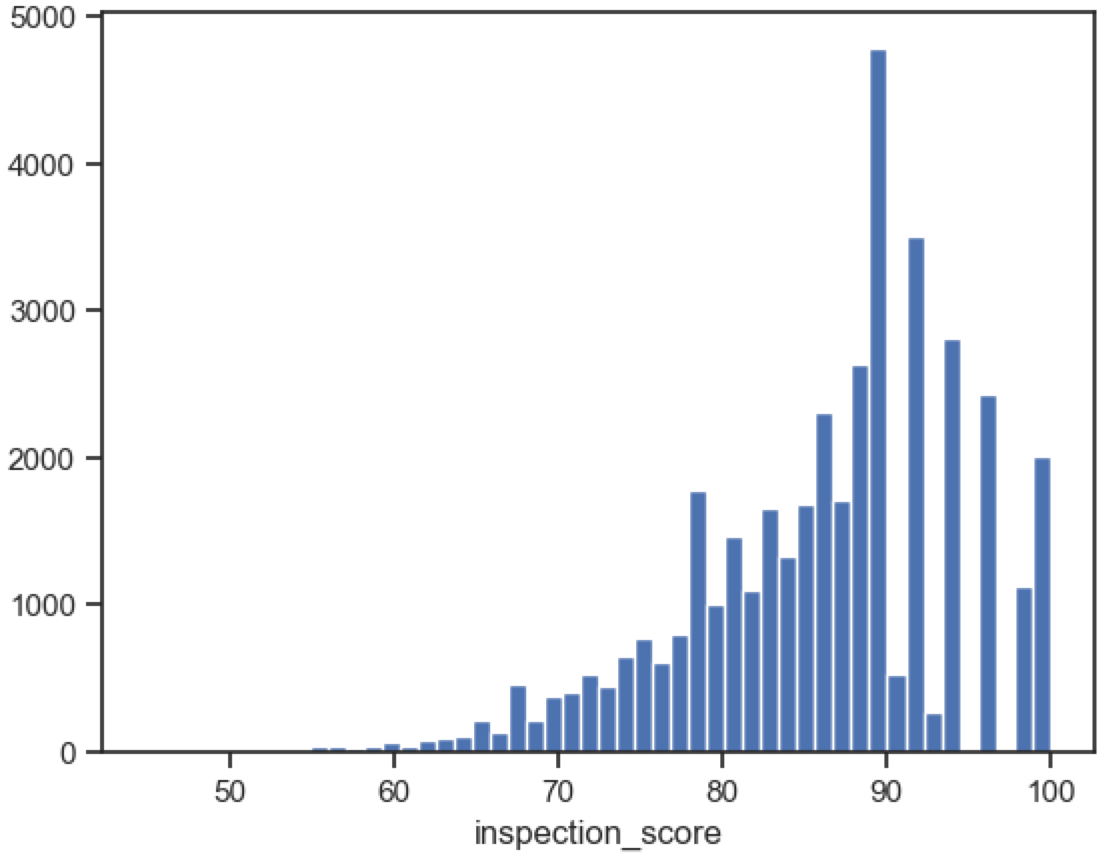
```
plt.xlabel(col)
plt.show()
```



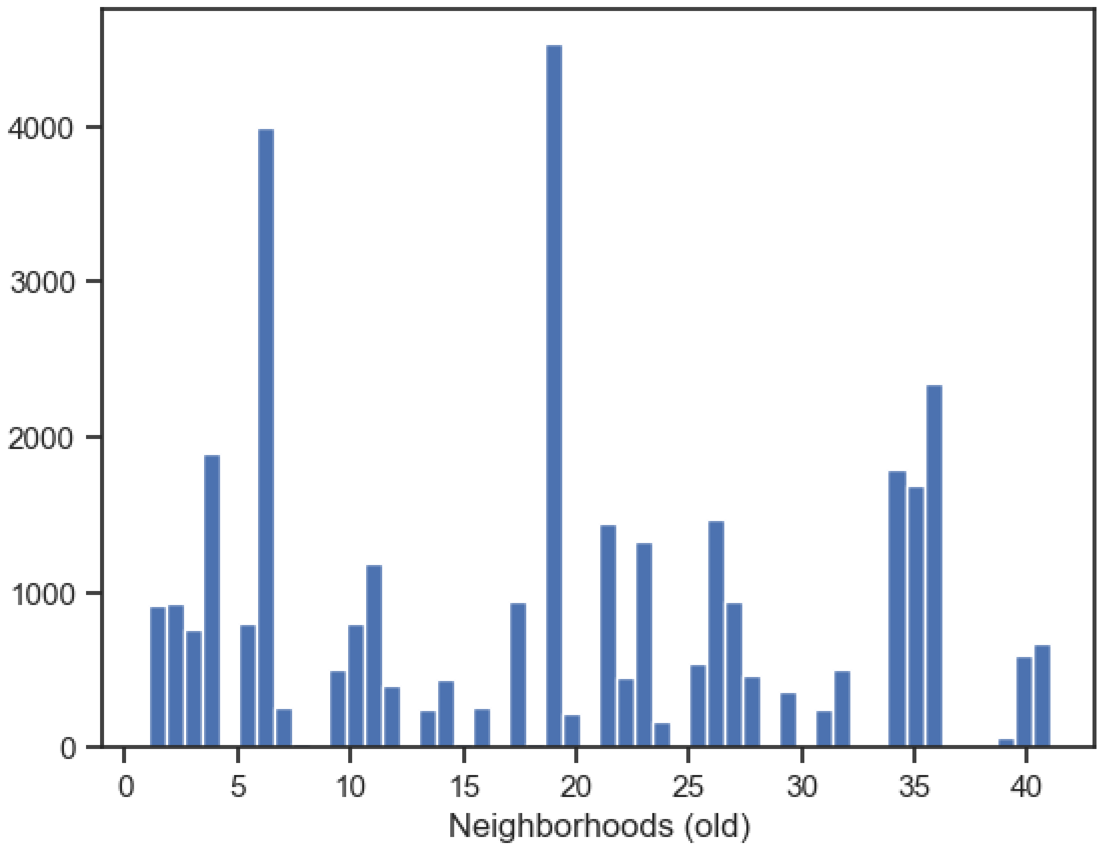

35000
30000
25000
20000
15000
10000
5000
0
−120
−100
−80
−60
−40
−20
0
business_longitude



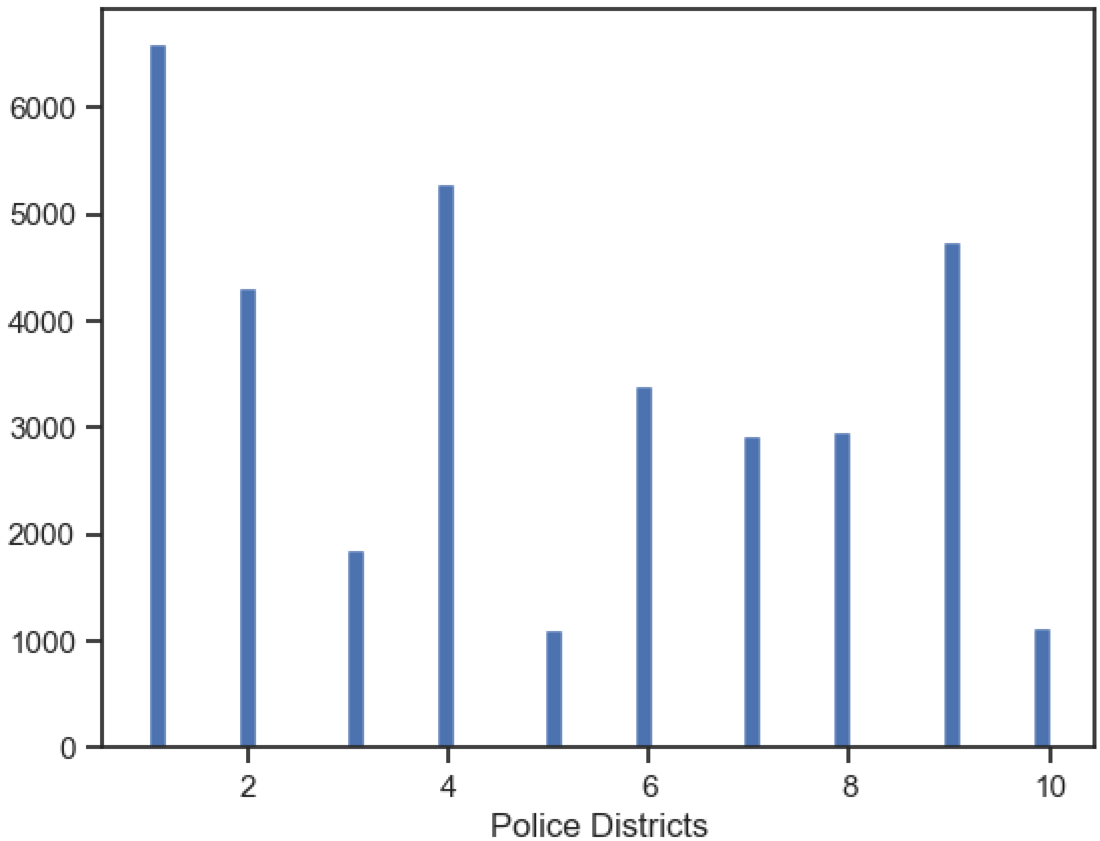
4000
3500
3000
2500
2000
1500
1000
500
0
1.4150
1.4152
1.4154
1.4156
1.4158
1.4160
1e10
business_phone_number

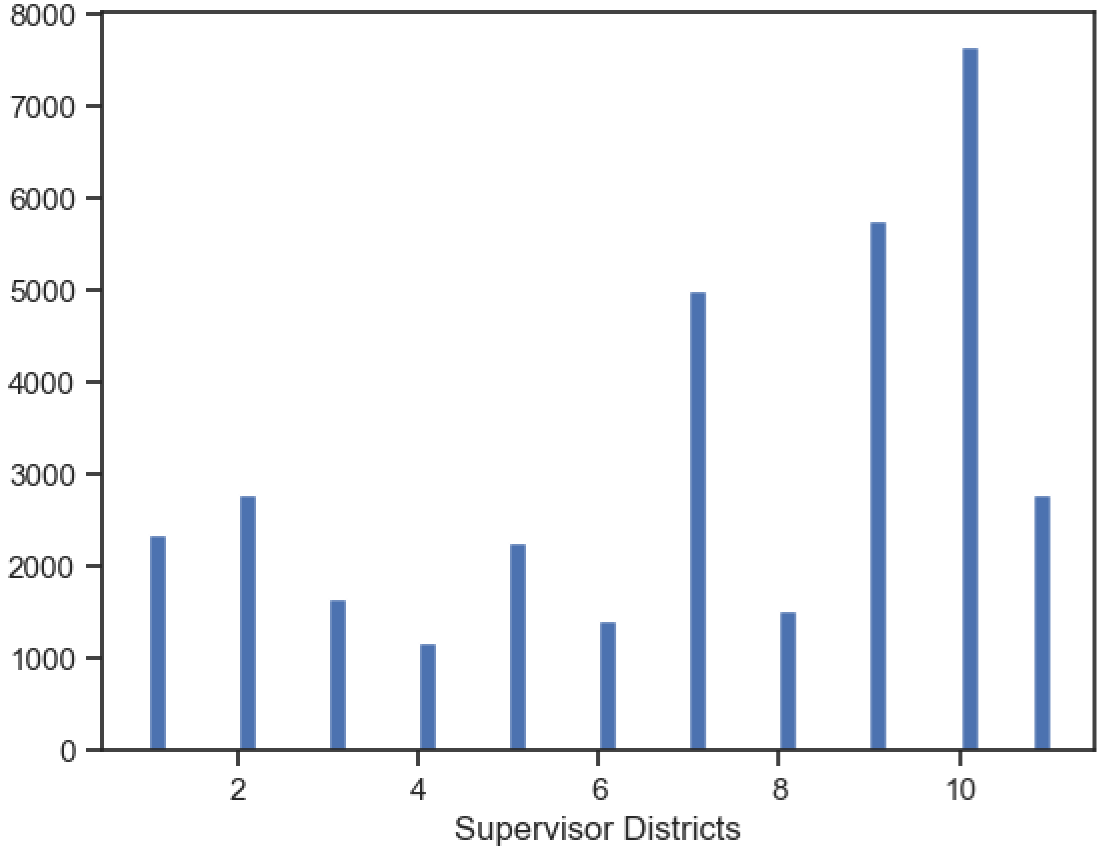


5000
4000
3000
2000
1000
0
50
60
70
80
90
100
inspection_score

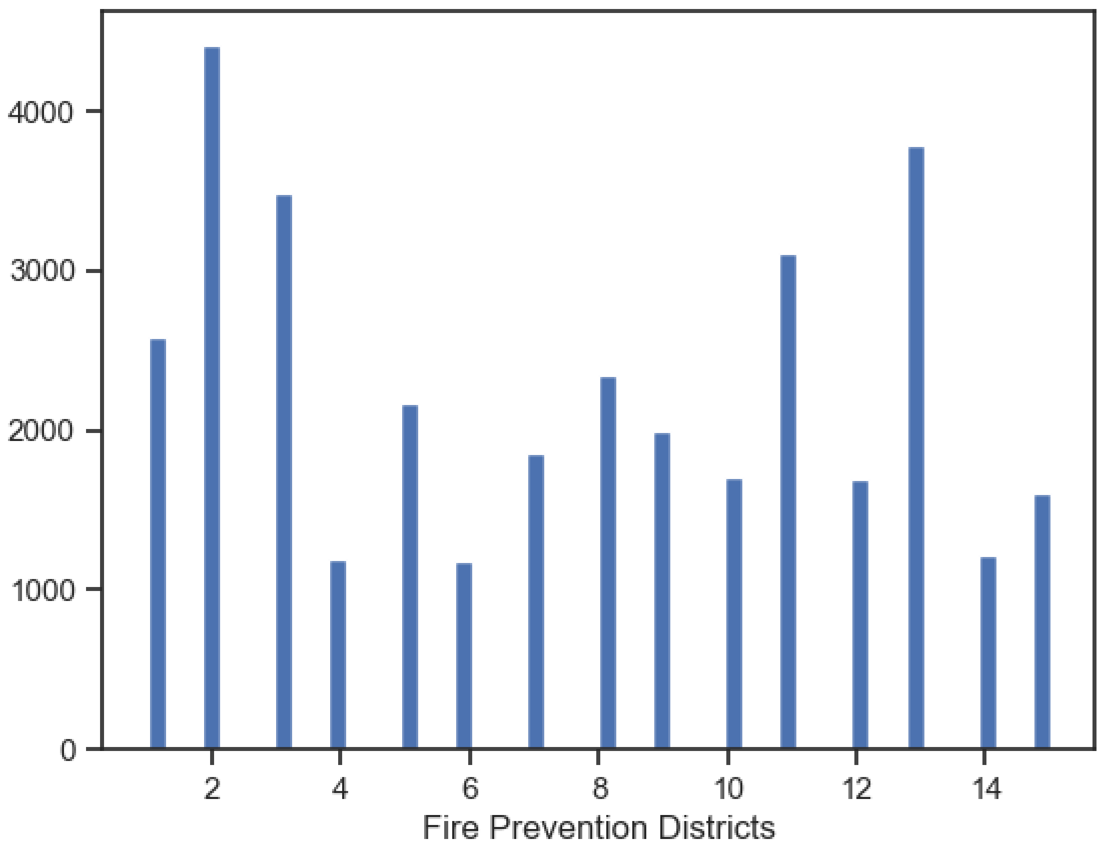


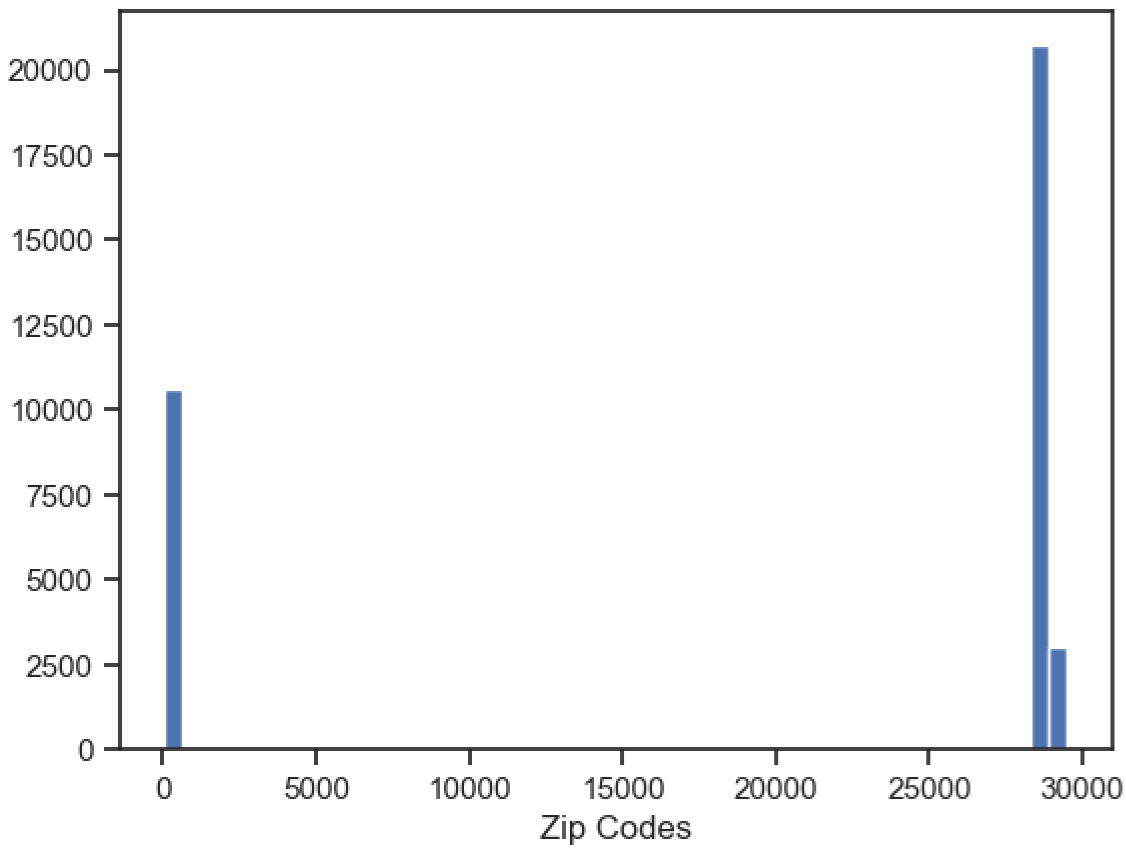
4000
3000
2000
1000
0
0
5
10
15
20
25
30
35
40
Neighborhoods (old)


6000
5000
4000
3000
2000
1000
0
2
4
6
8
10
Police Districts

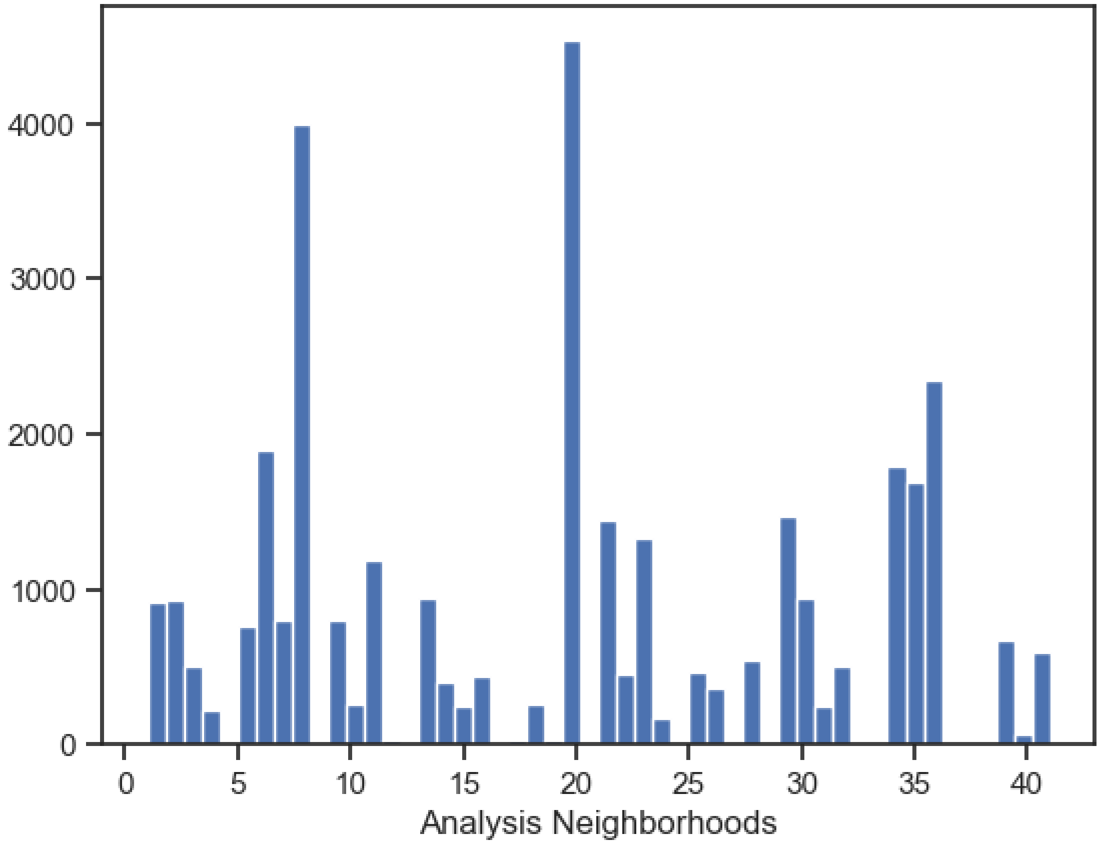


8000
7000
6000
5000
4000
3000
2000
1000
0
2
4
6
8
10
Supervisor Districts


4000
3000
2000
1000
0
2
4
6
8
10
12
14
Fire Prevention Districts



20000
17500
15000
12500
10000
7500
5000
2500
0
0
5000
10000
15000
20000
25000
30000
Zip Codes



Для обработки пропусков возьмем колонку Neighborhoods (old). Заметим, что данные распредлены волнами, поэтому для обработки будем использовать более сложную функцию, которая позволяет задавать колонку и вид импьютации

In [10]:

```
strategies=['mean', 'median', 'most_frequent']
```

In [11]:

```
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],
filled_data[filled_data.size-1]
```

In [12]:

```
test_num_impute_col(df, 'Neighborhoods (old)', strategies[0])
```

Out[12]:
```
('Neighborhoods (old)', 'mean', 19594, 19.048052590244044,
 19.048052590244044)
```

In [13]:

```
test_num_impute_col(df, 'Neighborhoods (old)', strategies[1])
```

Out[13]:
```
('Neighborhoods (old)', 'median', 19594, 19.0, 19.0)
```

In [14]:

```
test_num_impute_col(df, 'Neighborhoods (old)', strategies[2])
```

```
/Users/liza/opt/anaconda3/lib/python3.9/site-
packages/sklearn/impute/_base.py:49: FutureWarning: Unlike other reduction
functions (e.g. `skew`, `kurtosis`), the default behavior of `mode`
typically preserves the axis it acts along. In SciPy 1.11.0, this behavior
will change: the default value of `keepdims` will become False, the `axis`
over which the statistic is taken will be eliminated, and the value None
will no longer be accepted. Set `keepdims` to True or False to avoid this
warning.
  mode = stats.mode(array)
```

Out[14]:
```
('Neighborhoods (old)', 'most_frequent', 19594, 19.0, 19.0)
```

Заметим, что стратегии распределились одинаково, что было заметно и на графике, поэтому заполним пропуски медианой

In [15]:

```
df['Neighborhoods (old)'] = df['Neighborhoods
(old)'].fillna(df['Neighborhoods (old)'].median())
```

In [16]:

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

```
Колонка business_postal_code. Тип данных object. Количество пустых
значений 1018, 1.89%.
Колонка business_location. Тип данных object. Количество пустых значений
19556, 36.23%.
Колонка violation_id. Тип данных object. Количество пустых значений 12870,
23.85%.
Колонка violation_description. Тип данных object. Количество пустых
значений 12870, 23.85%.
```

Колонка risk_category. Тип данных object. Количество пустых значений 12870, 23.85%.

In [17]:

```
df_num = df[num_cols]
df_num
```

Out[17]:

	business_postal_code	business_location	violation_id	violation_description	risk_category
0	NaN	NaN	NaN	NaN	NaN
1	94118	NaN	97975_20190725_103124	Inadequately cleaned or sanitized food contact...	Moderate Risk
2	94110	NaN	NaN	NaN	NaN
3	94111	NaN	NaN	NaN	NaN
4	94109	NaN	85986_20161011_103114	High risk vermin infestation	High Risk
...	...	...	...	...	...
53968	94107	NaN	89569_20190506_103124	Inadequately cleaned or sanitized food contact...	Moderate Risk
53969	94132	NaN	NaN	NaN	NaN
53970	94105	NaN	84541_20190506_103133	Foods not protected from contamination	Moderate Risk
53971	94112	NaN	91572_20190506_103116	Inadequate food safety knowledge or lack of ce...	Moderate Risk
53972	94107	NaN	89569_20190506_103157	Food safety certificate or food handler card n...	Low Risk

53973 rows × 5 columns

In [18]:

```
cat_temp_data = df[['risk_category']]
cat_temp_data.head()
```

Out[18]:

	risk_category
0	NaN
1	Moderate Risk
2	NaN

3	NaN
4	High Risk

In [19]:

```
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

Out[19]:
```
array([['Low Risk'],
       ['Moderate Risk'],
       ['Low Risk'],
       ...,
       ['Moderate Risk'],
       ['Moderate Risk'],
       ['Low Risk']], dtype=object)
```

In [20]:

```
np.unique(data_imp2)
```

Out[20]:
```
array(['High Risk', 'Low Risk', 'Moderate Risk'], dtype=object)
```

In [22]:

```
col = ['High Risk', 'Low Risk', 'Moderate Risk']
for i in col:
    k = data_imp2[data_imp2==i].size
    print('Количество вхождений по {} равно {}'.format(i, k))
```

```
Количество вхождений по High Risk равно 5983
Количество вхождений по Low Risk равно 32375
Количество вхождений по Moderate Risk равно 15615
```

In [23]:

```
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant',
fill_value='Low Risk')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

Out[23]:
```
array([['Low Risk'],
       ['Moderate Risk'],
       ['Low Risk'],
       ...,
       ['Moderate Risk'],
       ['Moderate Risk'],
       ['Low Risk']], dtype=object)
```

Так количество пропусков > 10%, поэтому не до конца логично будет заполнять их самой встречающейся категорией, тк в дольнейшем это может исказить реальную картину данных, поэтому заполним пропуски Unknown

In [24]:

```
df['risk_category']= df['risk_category'].fillna('unk')
```

In [ ]: