РК ИУ5

Импорт библиотек

```
In [1]:
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
import warnings
warnings.filterwarnings('ignore')
sns.set(style="ticks")
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_absolute_error, mean_squared_error, median_absolute_err
or, r2_score
```

In [2]:

```
data = pd.read_csv('restaurant-scores-lives-standard.csv')
```

In [3]:

```
data['business_latitude'] = data['business_latitude'].replace(0,np.nan)
data['business_latitude'] = data['business_latitude'].fillna(data['business_latitude'].me
an())
data['Zip Codes'] = data['Zip Codes'].replace(0,np.nan)
data['Zip Codes'] = data['Zip Codes'].fillna(data['Zip Codes'].mean())
data['Supervisor Districts'] = data['Supervisor Districts'].replace(0,np.nan)
data['Supervisor Districts'] = data['Supervisor Districts'].fillna(data['Supervisor Districts'].mean())
```

In [4]:

```
data.head()
```

Out[4]:

business_id business_name business_address business_city business_state business_postal_code business_latitude bus

0	101192	Cochinita #2	2 Marina Blvd Fort Mason	San Francisco	CA	NaN	37.771619
1	97975	BREADBELLY	1408 Clement St	San Francisco	CA	94118	37.771619
2	92982	Great Gold Restaurant	3161 24th St.	San Francisco	CA	94110	37.771619
3	101389	HOMAGE	214 CALIFORNIA ST	San Francisco	CA	94111	37.771619
4	85986	Pronto Pizza	798 Eddy St	San Francisco	CA	94109	37.771619

5 rows × 23 columns

In [5]:

Out[5]: int64 business id business name object business address object business city object business state object object business_postal_code float64 business_latitude business_longitude float64 business_location object float64 business_phone_number object inspection id inspection_date object inspection_score float64 inspection_type object violation id object violation description object risk category object Neighborhoods (old) float64 Police Districts float64 Supervisor Districts float64 Fire Prevention Districts float64 Zin Codes float64 Analysis Neighborhoods float64 dtype: object In [6]: data.isnull().sum()

```
# проверим есть ли пропущенные значения
```

Out[6]:

business_id	0
business name	0
business address	0
business city	0
business state	0
business postal code	1018
business latitude	0
business longitude	19556
business location	19556
business phone number	36938
inspection id	0
inspection date	0
inspection score	13610
inspection type	0
violation id	12870
violation description	12870
risk category	12870
Neighborhoods (old)	19594
Police Districts	19594
Supervisor Districts	0
Fire Prevention Districts	19646
Zip Codes	0
Analysis Neighborhoods	19594
dtype: int64	

In [7]:

data.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 citv	53973 non-null	obiect

business_state 53973 non-null object 5 $\verb|business_postal_code|$ 52955 non-null object business latitude 53973 non-null float64 7 business longitude 34417 non-null float64 34417 non-null business location object 8 9 business phone number 17035 non-null float64 10 inspection id 53973 non-null object 11 53973 non-null inspection date 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 risk category 41103 non-null object 16 17 Neighborhoods (old) 34379 non-null float64 18 Police Districts 34379 non-null float64 19 Supervisor Districts 53973 non-null float64 20 Fire Prevention Districts 34327 non-null float64 53973 non-null 21 Zip Codes float64 22 Analysis Neighborhoods 34379 non-null float64 dtypes: float64(10), int64(1), object(12) memory usage: 9.5+ MB

In [8]:

data.head()

Out[8]:

business_id business_name business_address business_city business_state business_postal_code business_latitude bus

0	101192	Cochinita #2	2 Marina Blvd Fort Mason	San Francisco	CA	NaN	37.771619
1	97975	BREADBELLY	1408 Clement St	San Francisco	CA	94118	37.771619
2	92982	Great Gold Restaurant	3161 24th St.	San Francisco	CA	94110	37.771619
3	101389	HOMAGE	214 CALIFORNIA ST	San Francisco	CA	94111	37.771619
4	85986	Pronto Pizza	798 Eddy St	San Francisco	CA	94109	37.771619

5 rows × 23 columns

4

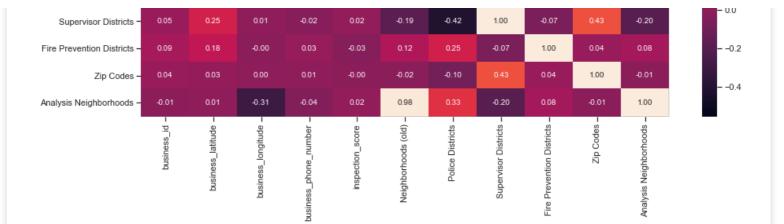
In [9]:

```
#Построим корреляционную матрицу
fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(data.corr(method='pearson'), ax=ax, annot=True, fmt='.2f')
```

Out[9]:

<AxesSubplot:>





In [10]:

```
X = data[["business_latitude","Zip Codes"]].astype(int)
Y = data["Supervisor Districts"].astype(int)
print('Входные данные:\n\n', X.head(), '\n\nВыходные данные:\n\n', Y.head())
```

Входные данные:

	business latitude	Zip Codes
0	37	20035
1	37	20035
2	37	20035
3	37	20035
4	37	20035

Выходные данные:

Name: Supervisor Districts, dtype: int64

In [11]:

Входные параметры обучающей выборки:

	business latitude	Zip Codes
24563	_ 37	56
19664	37	28858
37837	37	28858
33205	37	20035
42332	37	28859

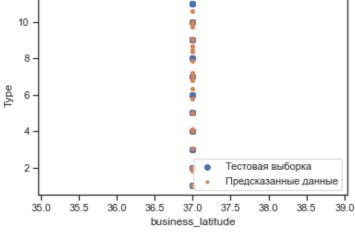
Входные параметры тестовой выборки:

	business latitude	Zip Codes
26331	_ 37	28859
23548	37	28859
51798	37	28862
34929	37	20035
13447	37	20035

Выходные параметры обучающей выборки:

```
24563 11
19664 1
37837 10
33205 7
```

```
7
42332
Name: Supervisor Districts, dtype: int64
Выходные параметры тестовой выборки:
 26331
23548
51798
         5
         7
34929
         7
13447
Name: Supervisor Districts, dtype: int64
In [12]:
from sklearn.svm import SVC , LinearSVC
from sklearn.pipeline import make pipeline
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler
In [13]:
from sklearn.ensemble import RandomForestRegressor
In [14]:
forest 1 = RandomForestRegressor(n estimators=5, oob score=True, random state=10)
forest 1.fit(X, Y)
Out[14]:
RandomForestRegressor(n estimators=5, oob score=True, random state=10)
In [15]:
Y predict = forest 1.predict(X test)
print('Средняя абсолютная ошибка:',
                                      mean_absolute_error(Y_test, Y_predict))
print('Средняя квадратичная ошибка:', mean squared error(Y test, Y predict))
print('Median absolute error:',
                                      median absolute error(Y test, Y predict))
print('Коэффициент детерминации:',
                                     r2 score(Y test, Y predict))
Средняя абсолютная ошибка: 0.5076807798166314
Средняя квадратичная ошибка: 1.757219197347261
Median absolute error: 0.06266219287253794
Коэффициент детерминации: 0.7249758023646331
In [16]:
plt.scatter(X test.business latitude, Y test, marker = 'o', label = 'Тестовая выборка
plt.scatter(X test.business latitude, Y predict, marker = '.', label = 'Предсказанные да
нные')
plt.legend(loc = 'lower right')
plt.xlabel('business latitude')
plt.ylabel('Type')
plt.show()
  10
                        9
   8
   6
```



```
In [17]:
```

```
svc = clf = make_pipeline(StandardScaler(), SVC(gamma='auto'))
svc.fit(X_train,Y_train)
```

Out[17]:

In [18]:

```
pred_y = svc.predict(X_test)
```

In [19]:

```
plt.scatter(X_test.business_latitude, Y_test, marker = 's', label = 'Тестовая выборка
')
plt.scatter(X_test.business_latitude, pred_y, marker = '.', label = 'Предсказанные данны
e')
plt.legend (loc = 'lower right')
plt.xlabel ('business_latitude')
plt.ylabel ('Type')
plt.show()
```

