РК 2. Харитонов А.А. ИУ5-64Б вариант 16

Задание. Для заданного набора данных постройте модели классификации или регрессии (в зависимости от конкретной задачи, рассматриваемой в наборе данных). Для построения моделей используйте методы линейной регрессии и градиентного бустинга. Оцените качество моделей на основе подходящих метрик качества (не менее двух метрик). Для построения моделей необходимо выполнить требуемую предобработку данных: заполнение пропусков, кодирование категориальных признаков, и т.д. Датасет: https://www.kaggle.com/san-francisco/sf-restaurant-scores-lives-standard

```python
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.preprocessing import LabelEncoder
from matplotlib import pyplot as plt
import seaborn as sns
```

```python
df = pd.read_csv('restaurant-scores.csv')
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
```

Выберем для анализа категории inspection_date, inspection_score, inspection_type, risk_category

```
df = df[['inspection_date', 'inspection_score', 'inspection_type',
'risk_category']]
df['inspection_date'] =
pd.to_datetime(df['inspection_date']).dt.strftime('%Y')

df.head()
```

```
  inspection_date  inspection_score        inspection_type
risk_category
0            2019               NaN          New Ownership
NaN
1            2019              96.0  Routine - Unscheduled  Moderate
Risk
2            2017               NaN          New Ownership
NaN
3            2019               NaN       New Construction
NaN
4            2016               NaN          New Ownership      High
Risk
```

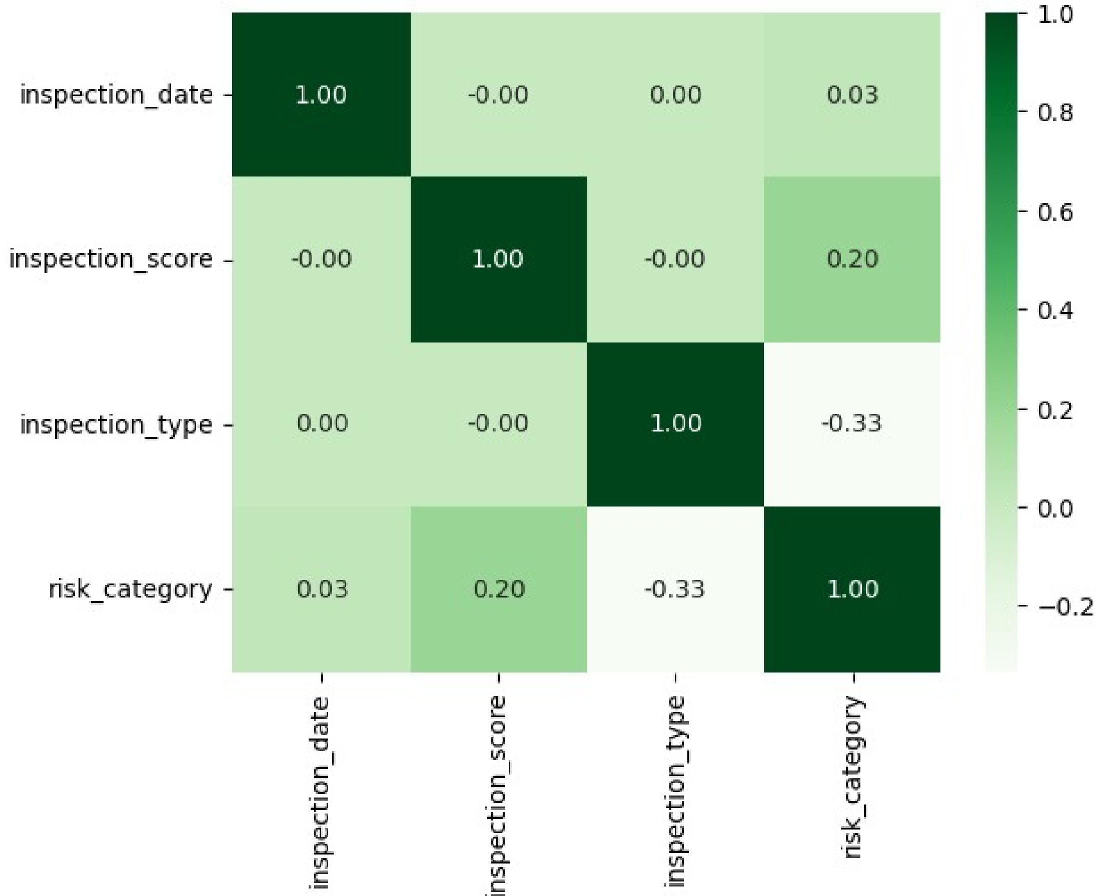
```
df['inspection_score'] =
df['inspection_score'].fillna(df['inspection_score'].mean())
df.nunique()
```

```
inspection_date      4
inspection_score    48
inspection_type     15
risk_category        3
dtype: int64
```

```
lb = LabelEncoder()
df['inspection_date'] = lb.fit_transform(df['inspection_date'])
df['inspection_type'] = lb.fit_transform(df['inspection_type'])
df['risk_category'] = lb.fit_transform(df['risk_category'])
```

```
corr = df.corr()
plt.figure()
sns.heatmap(corr, cbar=True, fmt='.2f', annot=True, cmap='Greens')
```

```
<AxesSubplot: >
```




```
x, y = df.drop(columns=['inspection_score']), df['inspection_score']
x_test, x_train, y_test, y_train = train_test_split(x, y, test_size =
0.2, random_state = 1)

gb = GradientBoostingRegressor()
gb.fit(x_train, y_train)
gb_pred = gb.predict(x_test)

lr = LinearRegression()
lr.fit(x_train, y_train)#
lr_pred = lr.predict(x_test)
```

Для сравнения качества моделей используем метрики средней абсолютной ошибки и коэффициента детерминации. Первый покажет, насколько предсказанные значения отклоняются от настоящих. Второй покажет, насколько точно модель предсказывает значения в целом.

```
lr_mae = mean_absolute_error(y_test, lr_pred)
gb_mae = mean_absolute_error(y_test, gb_pred)

lr_r2 = r2_score(y_test, lr_pred)
gb_r2 = r2_score(y_test, gb_pred)
```

```python
pd.DataFrame.from_dict({
    'LR': {
        'MAE': round(lr_mae, 5),
        'R2': f'{round(lr_r2 * 100, 3)}%'
    },
    'GB': {
        'MAE': round(gb_mae, 5),
        'R2': f'{round(gb_r2 * 100, 3)}%'
    }
})
```

```
          LR      GB
MAE  5.34598  4.3939
R2    4.299%  19.86%
```