

```

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import statsmodels.api as sm
import scipy.stats as stats

from sklearn.metrics import r2_score, mean_absolute_percentage_error
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

sns.set()
pd.options.display.max_columns = None

# sm.OLS(y, sm.add_constant(X)).fit().summary()

df = pd.read_csv("dataset_2task_final.csv")
df.head()

```

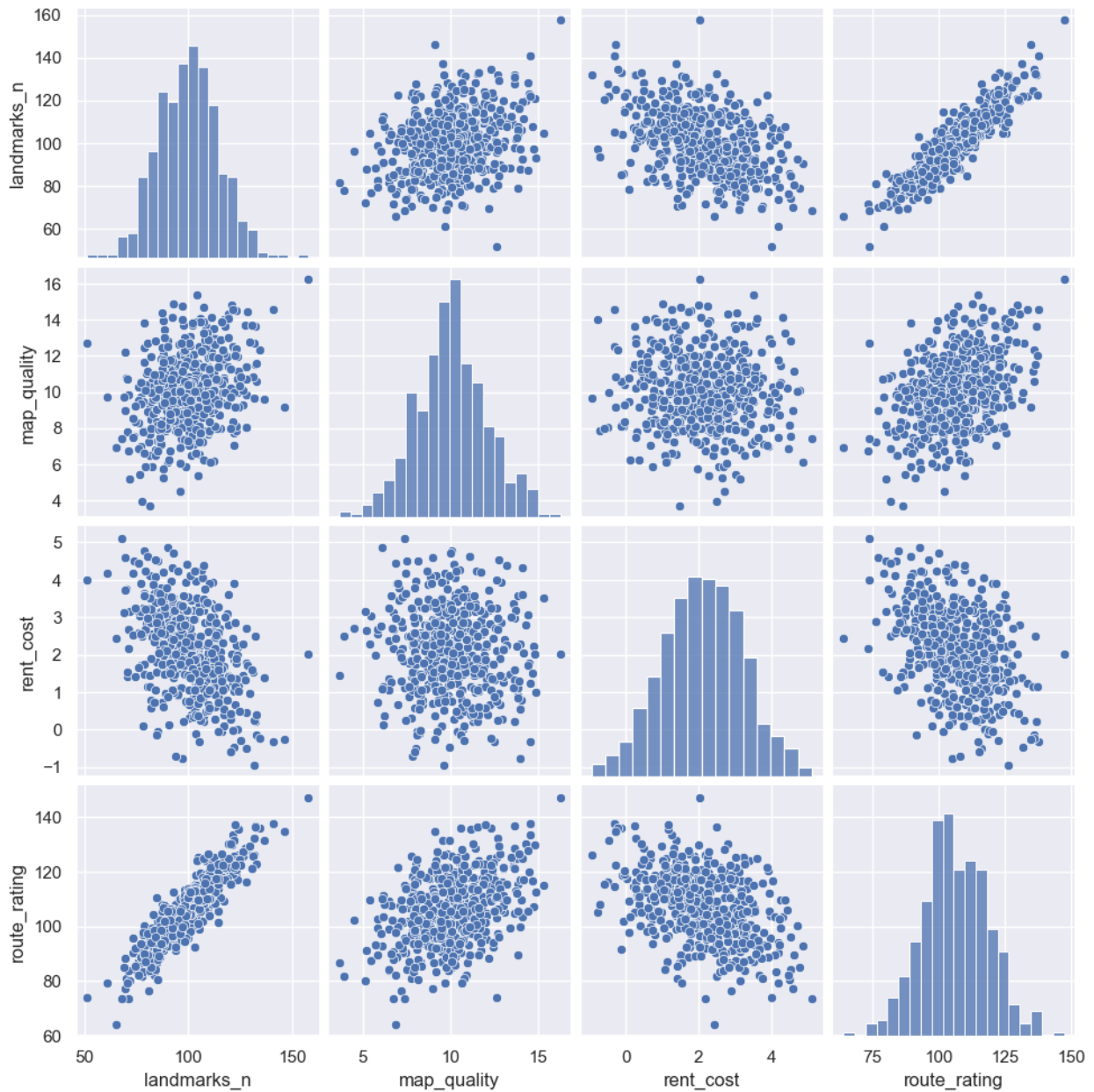
	landmarks_n	map_quality	rent_cost	route_rating
0	107.450712	12.224891	3.175834	116.521789
1	97.926035	13.715135	2.986853	104.642491
2	109.715328	7.688631	1.768171	106.745418
3	122.845448	12.268211	0.667700	124.682481
4	96.487699	8.523100	2.803592	100.959460

```

sns.pairplot(df)

<seaborn.axisgrid.PairGrid at 0x28344697af0>

```

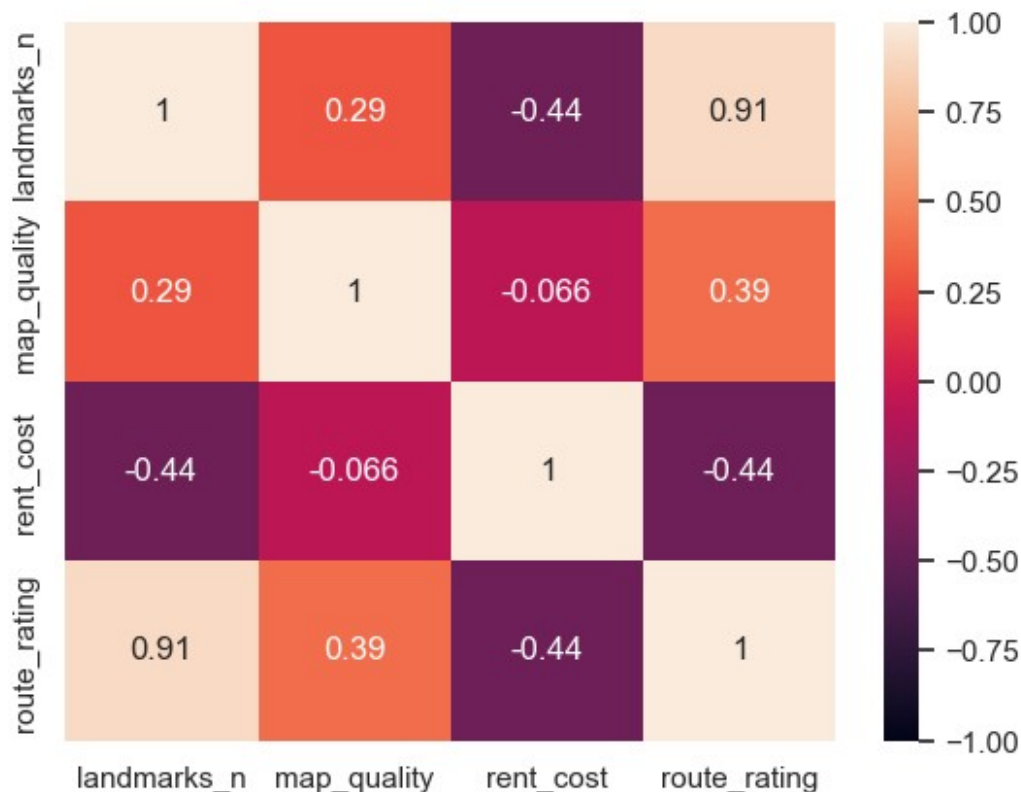


```
df.corr()
```

	landmarks_n	map_quality	rent_cost	route_rating
landmarks_n	1.000000	0.288614	-0.444132	0.909559
map_quality	0.288614	1.000000	-0.066426	0.387550
rent_cost	-0.444132	-0.066426	1.000000	-0.437450
route_rating	0.909559	0.387550	-0.437450	1.000000

```
sns.heatmap(df.corr(), vmin=-1, vmax=1, annot=True)
```

```
<Axes: >
```



```
df.columns
```

```
Index(['landmarks_n', 'map_quality', 'rent_cost', 'route_rating'],
      dtype='object')
```

из преданализа видно, что у целевой переменной route_rating есть сильно выраженная корреляция с landmarks_n (0.91), также выраженную линейную взаимосвязь видно из графиков pairplot, поэтому можно предположить что landmarks_n сильно влияет на route_rating

```
# model1
```

```
y = df["route_rating"]
```

```
X1 = sm.add_constant(df["map_quality"])
```

```
model1 = sm.OLS(y, X1).fit()
```

```
tab1 = model1.summary()
```

```
X2 = sm.add_constant(df[["map_quality", "landmarks_n"]])
```

```
model2 = sm.OLS(y, X2).fit()
```

```
tab2 = model2.summary()
```

```
X3 = sm.add_constant(df[["map_quality", "landmarks_n", "rent_cost"]])
```

```
model3 = sm.OLS(y, X3).fit()
```

```
tab3 = model3.summary()
```

tab1

из таблицы модели 1 видно, что : intercept = 82.2426 (t: 31.506, p_value: близко к 0) b1 = 2.3840 (t: 9.382, p_value: приблизительно 0)

rating = b1 * map_quality + intercept + e

e - необъясненный шум

```
tab1
<class 'statsmodels.iolib.summary.Summary'>
"""
                                OLS Regression Results
=====
Dep. Variable:                route_rating    R-squared:
0.150
Model:                        OLS           Adj. R-squared:
0.148
Method:                       Least Squares   F-statistic:
88.02
Date:                          Sun, 23 Nov 2025   Prob (F-statistic):
2.29e-19
Time:                          10:47:36         Log-Likelihood:
-1932.4
No. Observations:              500             AIC:
3869.
Df Residuals:                  498             BIC:
3877.
Df Model:                      1
Covariance Type:               nonrobust
=====
=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
const                82.2426         2.610      31.506      0.000      77.114
87.371
map_quality          2.3840         0.254       9.382      0.000      1.885
2.883
=====
=====
Omnibus:              0.511    Durbin-Watson:
1.979
Prob(Omnibus):        0.775    Jarque-Bera (JB):
```

```

0.621
Skew: -0.033 Prob(JB):
0.733
Kurtosis: 2.840 Cond. No.
52.3
=====
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""

```

tab2

из таблицы модели 2 видно, что : intercept = 23.6367 (t: 14.125, p_value: близко к 0) b1 = 0.8391 (t: 7.380, p_value: приблизительно 0) (map_quality) b2 = 0.7409 (t: 47.080, p_value: приблизительно 0) (landmarks_n)

rating = b2 * landmarks_n + b1 * map_quality + intercept + e

e - необъясненный шум

```

tab2

<class 'statsmodels.iolib.summary.Summary'>
"""
                                OLS Regression Results

=====
=====
Dep. Variable:                route_rating    R-squared:
0.844
Model:                        OLS            Adj. R-squared:
0.844
Method:                      Least Squares   F-statistic:
1348.
Date:                        Sun, 23 Nov 2025  Prob (F-statistic):
1.77e-201
Time:                        10:47:36        Log-Likelihood:
-1508.0
No. Observations:            500            AIC:
3022.
Df Residuals:                497            BIC:
3035.
Df Model:                    2

Covariance Type:            nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
const          23.6367      1.673      14.125      0.000      20.349
26.924
map_quality     0.8391      0.114       7.380      0.000      0.616
1.062
landmarks_n     0.7409      0.016     47.080      0.000      0.710
0.772
=====
=====
Omnibus:                1.740   Durbin-Watson:
2.016
Prob(Omnibus):          0.419   Jarque-Bera (JB):
1.616
Skew:                   -0.047   Prob(JB):
0.446
Kurtosis:               3.262   Cond. No.
768.
=====
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

"""

tab3

```

<class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

```

=====
=====
Dep. Variable:          route_rating   R-squared:
0.847
Model:                  OLS           Adj. R-squared:
0.846
Method:                 Least Squares   F-statistic:
912.1
Date:                  Sun, 23 Nov 2025   Prob (F-statistic):
2.15e-201
Time:                  10:47:36         Log-Likelihood:
-1504.5
No. Observations:      500             AIC:

```

```

3017.
Df Residuals:          496    BIC:
3034.
Df Model:              3

Covariance Type:      nonrobust

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
const          26.7211      2.026      13.190      0.000      22.741
30.702
map_quality      0.8608      0.113       7.598      0.000       0.638
1.083
landmarks_n      0.7201      0.017     41.238      0.000       0.686
0.754
rent_cost       -0.5842      0.219      -2.666      0.008     -1.015
-0.154
=====
=====
Omnibus:          1.985    Durbin-Watson:
2.017
Prob(Omnibus):    0.371    Jarque-Bera (JB):
1.843
Skew:             -0.076    Prob(JB):
0.398
Kurtosis:         3.256    Cond. No.
938.
=====
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""

```

tab3

из таблицы модели 3 видно, что : intercept = 26.7211 (t: 13.190, p_value: близко к 0)

b1 = 0.8608 (t: 7.598, p_value: приблизительно 0) (map_quality)

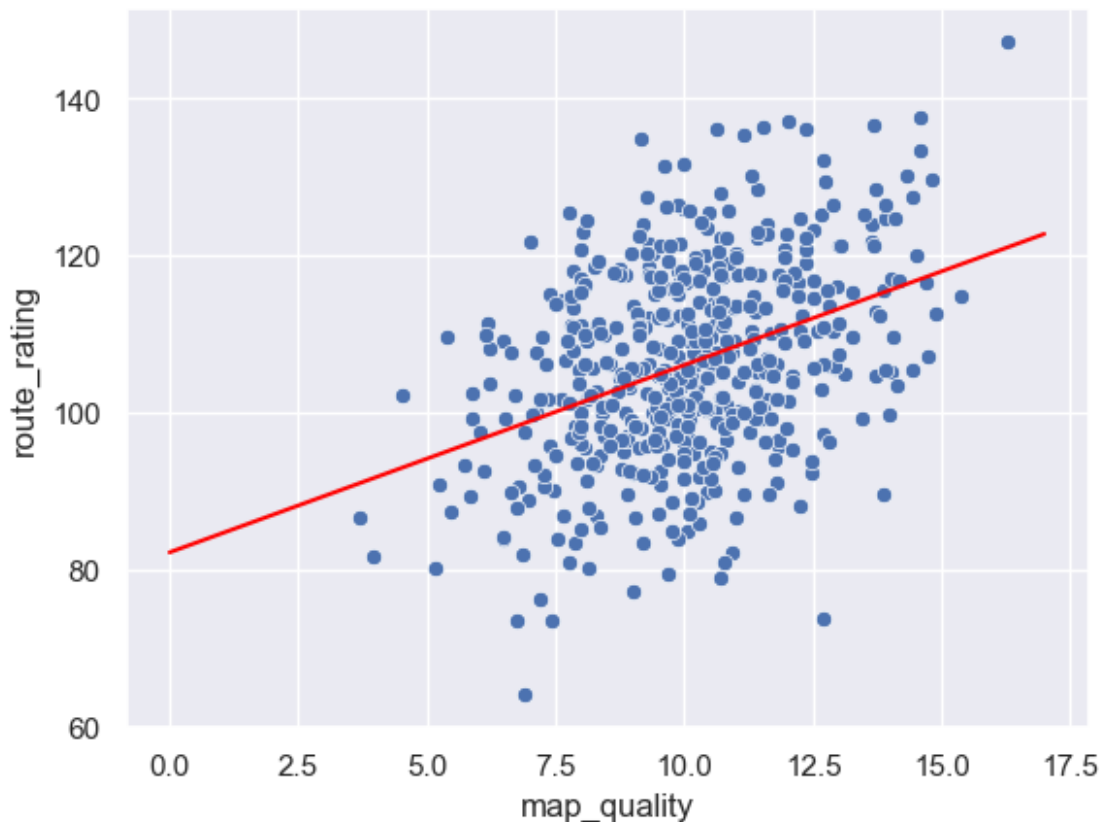
b2 = 0.7201 (t: 41.238, p_value: приблизительно 0) (landmarks_n)

b3 = -0.5842 (t: -2.666, p_value: приблизительно 0.008) (rent_cost)

$\text{rating} = b_3 * \text{rent_cost} + b_2 * \text{landmarks_n} + b_1 * \text{map_quality} + \text{intercept} + e$

e - необъясненный шум

```
def f(x):  
    return 82.2426 + 2.3840 * x  
  
x = np.linspace(0, 17, 100)  
y = list(map(f, x))  
  
sns.scatterplot(x=df["map_quality"], y=df["route_rating"])  
sns.lineplot(x=x, y=y, color="red")  
  
<Axes: xlabel='map_quality', ylabel='route_rating'>
```



на графике выше мы видим, что линейная связь между `map_quality` и `route_rating` не такая сильная и из-за этого немного отклонена от настоящего тренда, поэтому после добавления в модели 2 переменной `landmarks_n`, которая имеет сильную линейную взаимосвязь с целевой, коэффициент `b0` уменьшается

В модели 1: Большой `b0`, `b1` из-за слабой линейной взаимосвязи

В модели 2: Добавляется переменная имеющая сильную связь с целевой, поэтому значения `b1` и `b0` уменьшаются

В модели 3: В модели уже есть переменная связанная с целевой сильной линейной связью, поэтому добавление ещё одной переменной, имеющей невысокую линейную связь с целевой и не скоррелированной сильно с другими предикторами, практически не изменяет модель

В модели 2 мы видим, что R^2 равен 0.844, хотя в модели 1 он равен 0.150. Это объясняется тем, что добавляется переменная сильно связанная с целевой, что позволяет модели лучше описать изменчивость данных. В модели 3 R^2 равен 0.847 практически не изменяется, тк не нарушаются предположения линейной регрессии и добавленная переменная имеет умеренную взаимосвязь с целевой.

```
def scaler(x):
    return (x - x.mean()) / x.std()

df["route_rating"] = scaler(df["route_rating"])
df["rent_cost"] = scaler(df["rent_cost"])
df["landmarks_n"] = scaler(df["landmarks_n"])
df["map_quality"] = scaler(df["map_quality"])

df.mean().round(5)

landmarks_n    -0.0
map_quality    -0.0
rent_cost      -0.0
route_rating   -0.0
dtype: float64

df.std().round(5)

landmarks_n     1.0
map_quality     1.0
rent_cost       1.0
route_rating    1.0
dtype: float64

# model1

y = df["route_rating"]

X1 = sm.add_constant(df["map_quality"])
model1 = sm.OLS(y, X1).fit()
tab1 = model1.summary()

X2 = sm.add_constant(df[["map_quality", "landmarks_n"]])
model2 = sm.OLS(y, X2).fit()
tab2 = model2.summary()

X3 = sm.add_constant(df[["map_quality", "landmarks_n", "rent_cost"]])
model3 = sm.OLS(y, X3).fit()
tab3 = model3.summary()
```

```
tab1
```

```
<class 'statsmodels.iolib.summary.Summary'>
```

```
"""
```

OLS Regression Results

```
=====
```

```
=====
```

```
Dep. Variable:          route_rating    R-squared:
```

```
0.150
```

```
Model:                  OLS    Adj. R-squared:
```

```
0.148
```

```
Method:                 Least Squares    F-statistic:
```

```
88.02
```

```
Date:                  Sun, 23 Nov 2025    Prob (F-statistic):
```

```
2.29e-19
```

```
Time:                  11:33:04    Log-Likelihood:
```

```
-668.28
```

```
No. Observations:      500    AIC:
```

```
1341.
```

```
Df Residuals:          498    BIC:
```

```
1349.
```

```
Df Model:              1
```

```
Covariance Type:      nonrobust
```

```
=====
```

```
=====
```

```
              coef      std err          t      P>|t|      [0.025
```

```
0.975]
```

```
-----
```

```
-----
```

```
const          -1.527e-15      0.041   -3.7e-14      1.000      -0.081
```

```
0.081
```

```
map_quality      0.3875      0.041     9.382      0.000      0.306
```

```
0.469
```

```
=====
```

```
=====
```

```
Omnibus:              0.511    Durbin-Watson:
```

```
1.979
```

```
Prob(Omnibus):        0.775    Jarque-Bera (JB):
```

```
0.621
```

```
Skew:                -0.033    Prob(JB):
```

```
0.733
```

```
Kurtosis:            2.840    Cond. No.
```

```
1.00
```

```
=====
```

```
=====
```

```
Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

```
tab2
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
```

OLS Regression Results

```
=====
=====
```

```
Dep. Variable:          route_rating    R-squared:
0.844
Model:                  OLS            Adj. R-squared:
0.844
Method:                 Least Squares   F-statistic:
1348.
Date:                   Sun, 23 Nov 2025 Prob (F-statistic):
1.77e-201
Time:                   11:33:04        Log-Likelihood:
-243.93
No. Observations:       500            AIC:
493.9
Df Residuals:           497            BIC:
506.5
Df Model:                2
```

```
Covariance Type:        nonrobust
```

```
=====
=====
```

```
              coef      std err          t      P>|t|      [0.025
0.975]
```

```
-----
-----
```

```
const          -1.527e-15    0.018  -8.63e-14    1.000    -0.035
0.035
map_quality      0.1364      0.018    7.380    0.000     0.100
0.173
landmarks_n      0.8702      0.018   47.080    0.000     0.834
0.907
```

```
=====
=====
```

```
Omnibus:          1.740    Durbin-Watson:
2.016
Prob(Omnibus):     0.419    Jarque-Bera (JB):
1.616
Skew:              -0.047    Prob(JB):
0.446
```

Kurtosis: 3.262 Cond. No.
1.35

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

"""

tab3

<class 'statsmodels.iolib.summary.Summary'>

"""

OLS Regression Results

Dep. Variable: route_rating R-squared: 0.847
Model: OLS Adj. R-squared: 0.846
Method: Least Squares F-statistic: 912.1
Date: Sun, 23 Nov 2025 Prob (F-statistic): 2.15e-201
Time: 11:33:04 Log-Likelihood: -240.37
No. Observations: 500 AIC: 488.7
Df Residuals: 496 BIC: 505.6
Df Model: 3

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025
const	-1.532e-15	0.018	-8.72e-14	1.000	-0.035
map_quality	0.1399	0.018	7.598	0.000	0.104
landmarks_n	0.8459	0.021	41.238	0.000	0.806
rent_cost	-0.0525	0.020	-2.666	0.008	-0.091

```

=====
=====
Omnibus:                    1.985    Durbin-Watson:
2.017
Prob(Omnibus):              0.371    Jarque-Bera (JB):
1.843
Skew:                      -0.076    Prob(JB):
0.398
Kurtosis:                  3.256    Cond. No.
1.77
=====
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""

```

модель 1

coef	std err	t	P> t	[0.025
0.975]				

const -1.527e-15 0.041 -3.7e-14 1.000 -0.081 0.081

map_quality 0.3875 0.041 9.382 0.000 0.306 0.469

модель 2

coef	std err	t	P> t	[0.025
0.975]				

const -1.527e-15 0.018 -8.63e-14 1.000 -0.035 0.035 map_quality 0.1364 0.018 7.380 0.000
0.100 0.173 landmarks_n 0.8702 0.018 47.080 0.000 0.834 0.907

модель 3

coef	std err	t	P> t	[0.025
0.975]				

const -1.532e-15 0.018 -8.72e-14 1.000 -0.035 0.035 map_quality 0.1399 0.018 7.598 0.000
0.104 0.176 landmarks_n 0.8459 0.021 41.238 0.000 0.806 0.886 rent_cost -0.0525 0.020 -
2.666 0.008 -0.091 -0.014

Изменение интерпритации коэффициентов: Коэффициенты обозначают на сколько стандартных отклонений изменится рейтинг при изменении одного наблюдения на 1 стандартное отклонение

Динамика: Да, динамика поменялась, изменились единицы измерения

R2 До/После 1 0.150 0.150 2 0.844 0.844 3 0.847 0.847

Не изменился, данные не поменяли форму своего распределения, поэтому зависимости остались прежними

Добавление достопримечательностей сильно уменьшило коэффициент при прометке, механизм: люди сильнее формирую свое впечатление исходя из объектов ради которых они приехали, чем из удобств навигации

```
r = pd.DataFrame(np.random.uniform(low=-20, high=20, size=(500, 100)))
```

```
df1 = pd.concat([df, r], axis=1)
```

```
df1.head()
```

	landmarks_n	map_quality	rent_cost	route_rating		0
1 \						
0	0.499235	1.058435	0.950923	0.819942	9.687565	-15.077700
1	-0.147874	1.789997	0.783040	-0.128036	0.237954	-13.871729
2	0.653094	-1.168416	-0.299587	0.039779	1.458164	-5.957025
3	1.545159	1.079701	-1.277200	1.471172	19.603952	16.529862
4	-0.245595	-0.758775	0.620239	-0.421945	19.228614	10.998124
	2	3	4	5	6	7 \
0	9.807899	15.345861	-3.616467	7.245967	-16.022545	2.093153
1	-0.510739	-12.466214	16.436578	-8.685849	-14.706605	-15.072360
2	10.841322	-3.077807	9.164573	-10.862530	6.542134	-17.921809
3	0.059574	19.992759	16.022936	2.416236	16.159903	-8.073260
4	-12.169271	-6.957821	14.502267	-1.999887	-18.635762	18.072804
	8	9	10	11	12	13
14 \						
0	-12.061624	-2.385074	-14.327938	19.535791	6.276852	-14.001110
	7.215649					
1	19.869840	16.870688	11.887373	15.267239	0.305008	17.177949
	6.742402					
2	6.213017	-7.254765	-5.461104	17.027171	-9.872446	-17.545570
	7.465480					
3	-8.209458	-15.347937	2.251537	8.112514	-2.478972	-15.092095
	0.637841					

4	-4.640673	0.376672	-7.673550	8.781608	-14.027163	3.089642	-
5	1.198585						
	15	16	17	18	19	20	\
0	-4.246637	-6.141876	18.941572	-2.470243	9.384572	-0.008230	
1	7.015190	-0.575837	14.454814	8.327776	8.068590	5.790288	
2	9.277229	12.132074	-6.805107	2.024915	14.355088	1.149785	
3	-16.717171	-12.985877	0.798931	11.742207	5.872888	12.922478	
4	7.342800	-0.026099	-12.661201	8.395305	8.221292	12.965296	
	21	22	23	24	25	26	\
0	4.681619	4.860797	10.660121	12.155133	4.788524	1.676406	
1	-3.364807	14.021271	-10.789163	13.012118	-11.955435	-6.335035	
2	-12.070870	-13.953790	-3.761965	19.033987	-7.494352	-9.201671	
3	-12.108567	-18.560016	18.183767	-0.204688	6.895192	-1.472702	
4	-8.246712	-9.628701	0.984894	13.342117	6.137731	-11.088617	
	27	28	29	30	31	32	\
0	13.955174	-1.740969	8.763383	9.239703	4.340067	1.617358	
1	-2.210918	-7.529933	15.366828	8.983874	-15.486723	-16.315871	
2	-19.320414	4.174414	15.529789	-4.710205	-9.496840	4.166692	
3	1.332896	4.832032	-18.494489	14.523254	-10.300963	-5.578027	
4	7.670607	-19.026373	10.178464	7.965304	2.060783	5.252590	
	33	34	35	36	37	38	\
0	-4.712244	-14.380543	18.728836	-16.616867	-18.856118	14.674925	
1	10.720024	-5.574229	18.179451	-5.976350	1.819036	-0.082825	
2	8.262789	-6.989262	9.090527	16.905891	-11.846503	-17.003148	
3	-2.193200	18.295847	17.991172	-3.907350	-2.730131	-1.758283	
4	-2.918473	10.611843	-16.444574	4.611071	6.241343	-15.990121	
	39	40	41	42	43	44	\
0	-17.796935	-2.431664	3.423063	13.710956	13.651729	-14.032448	
1	14.273996	-18.764746	-19.921959	6.720883	-7.965068	4.751117	
2	-9.818689	-4.801657	-2.999662	13.343683	-11.961649	-9.388744	
3	10.105505	6.386715	-15.721233	7.337470	-10.728884	13.294580	
4	15.975162	-16.350222	9.995839	-8.756302	5.178609	13.065698	
	45	46	47	48	49	50	\
0	-3.000625	0.644364	-19.052475	-7.949468	3.361612	6.283890	
1	16.487637	-2.984978	-14.199044	-11.248484	-17.151497	1.094632	
2	17.658123	1.046835	13.750674	-1.312696	18.038397	-16.077943	
3	-12.942474	-13.315688	9.113363	-18.200745	5.312336	-3.856733	
4	-11.696887	-1.181166	17.047110	-19.373196	1.100285	-5.546338	
	51	52	53	54	55	56	
57	\						
0	15.428426	2.612801	2.283896	-8.831240	10.220180	2.356648	
9	5.594271						
1	12.295145	13.583029	-0.084389	-16.894031	-11.835956	11.705194	

4.055662
2 -13.240584 -10.849785 11.835438 -10.927281 -12.601026 -4.614408 -
0.942986
3 -16.206304 8.613329 -12.764994 -5.541527 -0.623068 -14.313358 -
0.909231
4 3.997920 -16.244382 5.041687 -19.995932 1.102720 11.392678
2.860693

	58	59	60	61	62	63	\
0	-12.357211	5.609484	-7.069887	-11.693114	8.545285	-17.044708	
1	-5.221373	-19.474118	-16.244572	9.264766	-10.539283	-15.036543	
2	12.336374	-2.245685	2.622721	-19.569003	-6.234705	13.561594	
3	2.686551	-8.091812	10.290316	2.362837	-19.389279	-6.319503	
4	-12.256429	5.865048	10.725391	13.470601	1.637323	-10.080043	

	64	65	66	67	68	69	\
0	-7.652989	-13.483117	2.116547	-16.266500	1.046057	-14.690019	
1	-16.566891	5.461465	-8.223505	-10.665957	14.146907	-18.410311	
2	0.299797	4.289208	8.284500	0.151856	-9.684972	-1.742955	
3	17.345183	-9.424323	12.961479	17.677573	8.768751	10.656302	
4	14.135203	18.330741	-2.442494	13.942819	11.781188	-14.655544	

	70	71	72	73	74	75	\
0	7.858034	1.207239	-5.479742	-6.192626	-5.281844	-17.540304	
1	-4.826425	8.796274	-14.438025	-9.096596	8.983718	15.683404	
2	7.620522	9.951896	-1.037972	-9.127836	-17.520821	-6.357475	
3	-11.697355	17.621816	-9.314951	9.436022	18.538744	8.433698	
4	19.842606	9.021166	-11.956609	-13.937289	-7.360500	-2.348843	

	76	77	78	79	80	81	\
0	12.877849	12.158057	7.981776	17.910982	-17.661260	-4.839192	
1	-19.969711	7.856720	1.038945	6.899395	-3.630170	-9.942430	
2	-12.066206	19.631006	-3.178366	-13.346312	4.778866	14.090306	
3	6.288490	-7.346911	14.119315	-9.114039	-13.745054	12.399063	
4	2.763464	1.305838	3.130072	-9.879733	5.070055	10.872274	

	82	83	84	85	86	87	\
0	11.624087	9.069959	-9.573394	-4.752855	16.778179	-13.118966	
1	-14.413988	13.991259	13.067873	18.031663	-2.300623	-11.959986	
2	-1.069039	-19.088044	-13.538196	-4.387265	6.659399	18.370502	
3	12.013144	7.761703	-18.136011	-6.677388	16.866716	2.188810	
4	-15.198154	2.053250	1.429537	11.861143	8.181338	2.057933	

	88	89	90	91	92	93	\
0	13.036413	2.145837	17.416757	4.108037	8.151335	16.185133	
1	-11.910800	1.901780	-4.647540	-13.915618	-9.240361	-7.199250	
2	4.777913	-16.043641	-13.609996	9.220980	-5.258637	-13.859394	
3	-3.001197	-4.105661	-7.247537	1.218976	4.698488	-0.839964	
4	-14.155085	-3.873919	12.406653	0.511814	13.890510	13.667269	

	94	95	96	97	98	99
0	14.279869	10.377212	-1.542171	-1.519252	-19.969274	-17.336690
1	1.086564	-1.748646	15.992691	-4.814905	3.528778	-2.829255
2	1.563921	-12.486986	10.514131	17.019963	18.586428	8.566414
3	2.931654	18.376224	-7.193748	-7.295949	-14.032403	2.210238
4	3.493981	2.460247	5.570439	1.758346	9.068501	0.559029

```
# model1
```

```
y = df1["route_rating"]
```

```
X = sm.add_constant(df1.drop(columns=["route_rating"]))
```

```
model = sm.OLS(y, X).fit()
```

```
tab = model.summary()
```

```
tab
```

```
<class 'statsmodels.iolib.summary.Summary'>
```

```
"""
```

OLS Regression Results

```
=====
```

```
=====
```

```
Dep. Variable:          route_rating    R-squared:
0.877
```

```
Model:                  OLS    Adj. R-squared:
0.845
```

```
Method:                 Least Squares    F-statistic:
27.36
```

```
Date:                  Sun, 23 Nov 2025    Prob (F-statistic):
2.26e-130
```

```
Time:                  11:54:55    Log-Likelihood:
-185.48
```

```
No. Observations:          500    AIC:
579.0
```

```
Df Residuals:              396    BIC:
1017.
```

```
Df Model:                  103
```

```
Covariance Type:          nonrobust
```

```
=====
```

```
=====
```

	coef	std err	t	P> t	[0.025
0.975]					

```
-----
```

```
-----
```

const	-0.0046	0.019	-0.240	0.810	-0.042
-------	---------	-------	--------	-------	--------

```
0.033
```

landmarks_n	0.8515	0.023	37.201	0.000	0.807
-------------	--------	-------	--------	-------	-------

0.897					
map_quality	0.1470	0.020	7.246	0.000	0.107
0.187					
rent_cost	-0.0444	0.022	-1.993	0.047	-0.088
-0.001					
0	0.0003	0.002	0.188	0.851	-0.003
0.004					
1	-0.0021	0.002	-1.259	0.209	-0.005
0.001					
2	-0.0009	0.002	-0.541	0.589	-0.004
0.002					
3	-0.0028	0.002	-1.637	0.102	-0.006
0.001					
4	0.0032	0.002	1.866	0.063	-0.000
0.007					
5	0.0003	0.002	0.146	0.884	-0.003
0.004					
6	-0.0010	0.002	-0.624	0.533	-0.004
0.002					
7	-0.0019	0.002	-1.153	0.250	-0.005
0.001					
8	9.849e-05	0.002	0.058	0.954	-0.003
0.003					
9	0.0016	0.002	0.978	0.329	-0.002
0.005					
10	0.0006	0.002	0.364	0.716	-0.003
0.004					
11	-0.0015	0.002	-0.893	0.373	-0.005
0.002					
12	-0.0014	0.002	-0.841	0.401	-0.005
0.002					
13	-0.0006	0.002	-0.371	0.711	-0.004
0.003					
14	-0.0022	0.002	-1.289	0.198	-0.006
0.001					
15	-0.0006	0.002	-0.363	0.716	-0.004
0.003					
16	0.0016	0.002	0.945	0.345	-0.002
0.005					
17	0.0010	0.002	0.545	0.586	-0.003
0.004					
18	0.0009	0.002	0.512	0.609	-0.003
0.004					
19	0.0008	0.002	0.487	0.627	-0.003
0.004					
20	0.0019	0.002	1.065	0.287	-0.002
0.005					
21	-0.0044	0.002	-2.531	0.012	-0.008
-0.001					

22 0.002	-0.0013	0.002	-0.766	0.444	-0.005
23 0.003	-0.0004	0.002	-0.228	0.820	-0.004
24 0.007	0.0036	0.002	1.991	0.047	4.48e-05
25 0.003	-0.0007	0.002	-0.438	0.662	-0.004
26 0.005	0.0021	0.002	1.264	0.207	-0.001
27 0.002	-0.0011	0.002	-0.640	0.523	-0.005
28 0.000	-0.0031	0.002	-1.742	0.082	-0.007
29 0.002	-0.0015	0.002	-0.870	0.385	-0.005
30 0.005	0.0011	0.002	0.644	0.520	-0.002
31 0.002	-0.0014	0.002	-0.829	0.408	-0.005
32 0.005	0.0017	0.002	0.963	0.336	-0.002
33 0.001	-0.0026	0.002	-1.549	0.122	-0.006
34 0.003	-6.632e-05	0.002	-0.038	0.969	-0.003
35 0.004	0.0005	0.002	0.259	0.796	-0.003
36 0.002	-0.0018	0.002	-1.036	0.301	-0.005
37 0.004	0.0003	0.002	0.198	0.843	-0.003
38 0.004	0.0003	0.002	0.200	0.841	-0.003
39 0.000	-0.0029	0.002	-1.743	0.082	-0.006
40 0.003	0.0002	0.002	0.092	0.926	-0.003
41 0.006	0.0028	0.002	1.603	0.110	-0.001
42 0.002	-0.0009	0.002	-0.545	0.586	-0.004
43 0.001	-0.0029	0.002	-1.621	0.106	-0.006
44 0.001	-0.0022	0.002	-1.275	0.203	-0.006
45 0.001	-0.0029	0.002	-1.671	0.096	-0.006
46	-0.0002	0.002	-0.097	0.923	-0.004

0.003					
47	0.0007	0.002	0.406	0.685	-0.003
0.004					
48	-0.0024	0.002	-1.409	0.160	-0.006
0.001					
49	-0.0011	0.002	-0.666	0.506	-0.004
0.002					
50	-5.95e-05	0.002	-0.034	0.973	-0.003
0.003					
51	-0.0007	0.002	-0.414	0.679	-0.004
0.003					
52	0.0010	0.002	0.588	0.557	-0.002
0.004					
53	-0.0034	0.002	-1.966	0.050	-0.007
-5.51e-07					
54	0.0014	0.002	0.812	0.417	-0.002
0.005					
55	0.0019	0.002	1.078	0.282	-0.002
0.005					
56	0.0004	0.002	0.272	0.786	-0.003
0.004					
57	-0.0002	0.002	-0.089	0.929	-0.004
0.003					
58	-0.0022	0.002	-1.303	0.193	-0.005
0.001					
59	0.0005	0.002	0.288	0.773	-0.003
0.004					
60	0.0026	0.002	1.511	0.132	-0.001
0.006					
61	-0.0023	0.002	-1.384	0.167	-0.006
0.001					
62	0.0039	0.002	2.209	0.028	0.000
0.007					
63	0.0009	0.002	0.522	0.602	-0.002
0.004					
64	0.0009	0.002	0.544	0.586	-0.002
0.004					
65	0.0029	0.002	1.689	0.092	-0.000
0.006					
66	0.0011	0.002	0.706	0.481	-0.002
0.004					
67	-0.0009	0.002	-0.552	0.581	-0.004
0.002					
68	0.0010	0.002	0.587	0.558	-0.002
0.004					
69	0.0017	0.002	0.979	0.328	-0.002
0.005					
70	-4.707e-05	0.002	-0.029	0.977	-0.003
0.003					

71	-0.0037	0.002	-2.158	0.032	-0.007
-0.000					
72	-0.0010	0.002	-0.576	0.565	-0.004
0.002					
73	-0.0021	0.002	-1.218	0.224	-0.006
0.001					
74	-0.0012	0.002	-0.695	0.488	-0.005
0.002					
75	-0.0009	0.002	-0.558	0.577	-0.004
0.002					
76	-0.0024	0.002	-1.416	0.158	-0.006
0.001					
77	0.0008	0.002	0.440	0.660	-0.003
0.004					
78	-0.0017	0.002	-0.983	0.326	-0.005
0.002					
79	-0.0002	0.002	-0.151	0.880	-0.004
0.003					
80	-0.0007	0.002	-0.383	0.702	-0.004
0.003					
81	-0.0002	0.002	-0.110	0.913	-0.004
0.003					
82	-0.0008	0.002	-0.452	0.652	-0.004
0.003					
83	0.0001	0.002	0.083	0.934	-0.003
0.003					
84	-0.0031	0.002	-1.703	0.089	-0.007
0.000					
85	0.0017	0.002	1.046	0.296	-0.001
0.005					
86	-0.0016	0.002	-0.916	0.360	-0.005
0.002					
87	0.0025	0.002	1.461	0.145	-0.001
0.006					
88	0.0014	0.002	0.842	0.400	-0.002
0.005					
89	0.0024	0.002	1.379	0.169	-0.001
0.006					
90	-0.0005	0.002	-0.279	0.781	-0.004
0.003					
91	-0.0026	0.002	-1.477	0.140	-0.006
0.001					
92	-0.0014	0.002	-0.799	0.425	-0.005
0.002					
93	0.0021	0.002	1.264	0.207	-0.001
0.005					
94	-0.0010	0.002	-0.571	0.568	-0.004
0.002					
95	0.0014	0.002	0.825	0.410	-0.002

```

0.005
96          -0.0022      0.002      -1.303      0.193      -0.006
0.001
97          -0.0004      0.002      -0.239      0.812      -0.004
0.003
98          -0.0015      0.002      -0.910      0.363      -0.005
0.002
99          -0.0016      0.002      -0.938      0.349      -0.005
0.002
=====
=====
Omnibus:                0.912    Durbin-Watson:
2.106
Prob(Omnibus):          0.634    Jarque-Bera (JB):
0.738
Skew:                   -0.078    Prob(JB):
0.691
Kurtosis:               3.106    Cond. No.
25.9
=====
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
0.877

```

R2 стал 0.877, он выше, это не означает, что модель стала лучше, тк например это могло вызвано случайностью или прочим