J	Вариант: 23; Задача: 3; Задача 3 Для заданного набора данных пр		данных (для олнс	ого признака) и пре	образование кате	гориальн
Γ <i>ν</i>	признаков в количественные дву использовали для решения задач	умя способами (label encoding, чи и почему?	one hot encoding	g) для одного призн	ака. Какие методь	-
		ayyıe.com/mohansack	ıarya/gradu	iate-admission		
	<pre>import pandas as pd import seaborn as sns import matplotlib.pyplot as prom sklearn.impute import Si from sklearn.impute import Mi import warnings</pre>	<pre>impleImputer issingIndicator</pre>				
[2].	<pre>import warnings warnings.filterwarnings('ignorates) sns.set(style="ticks") %matplotlib inline  data = pd.read_csv('restaurane)</pre>		•			
[3]: [3]:	data.head()	siness_address business_city bus		ess_postal code bear	ness_latitude busin	ess_longit
	business_id business_name bus  101192 Cochinita #2	2 Marina Blvd Fort Mason San Francisco	iness_state busine	ess_postal_code busii	ness_latitude busine	ess_longitu
	1 97975 BREADBELLY 1- 2 92982 Great Gold Restaurant	408 Clement St San Francisco  3161 24th St. San Francisco	CA	94118 94110	NaN NaN	N
	<ul> <li>3 101389 HOMAGE</li> <li>4 85986 Pronto Pizza</li> </ul>	14 CALIFORNIA ST San Francisco 798 Eddy St San Francisco	CA	94111 94109	NaN NaN	N
[4]:	rows × 23 columns  data.dtypes					
[4]:	business_id business_name business_address business_city	<pre>int64 object object object</pre>				
	business_longitude business_location	object object float64 float64 object float64 object				
	inspection_date	object float64 object object object object object object				
	Neighborhoods (old) Police Districts Supervisor Districts Fire Prevention Districts Zip Codes	float64 float64 float64 float64 float64 float64				
[5]:	dtype: object  data.isnull().sum()  # проверим есть ли пропущення	ые значения				
	<pre>business_id business_name business_address business_city business_state business_postal_code</pre>	<ul> <li>0</li> <li>0</li> <li>0</li> <li>0</li> <li>0</li> <li>1018</li> </ul>				
	business_longitude business_location business_phone_number inspection_id inspection_date	19556 19556 19556 36938 0				
	<pre>inspection_type violation_id violation_description risk_category Neighborhoods (old)</pre>	13610 0 12870 12870 12870 19594				
	Supervisor Districts Fire Prevention Districts Zip Codes	19594 19594 19646 19576 19594				
[6]:	<pre>data.info()  <class 'pandas.core.frame.data="" (total="" 0="" 23="" 53973="" column<="" columns="" data="" entries,="" pre="" rangeindex:=""></class></pre>	to 53972 s):				
	<pre># Column 0 business_id 1 business_name 2 business_address 3 business_city</pre>	Non-Null Count Dtype 53973 non-null int64 53973 non-null object 53973 non-null object 53973 non-null object				
	<pre>4 business_state 5 business_postal_code 6 business_latitude 7 business_longitude 8 business_location 9 business_phone_number</pre>	53973 non-null object 52955 non-null object 34417 non-null float64 34417 non-null float64 34417 non-null object 17035 non-null float64				
	10 inspection_id 11 inspection_date 12 inspection_score 13 inspection_type 14 violation_id 15 violation_description	53973 non-null object 53973 non-null object 40363 non-null float64 53973 non-null object 41103 non-null object 41103 non-null object				
	16 risk_category 17 Neighborhoods (old) 18 Police Districts 19 Supervisor Districts	41103 non-null object 34379 non-null float64 34379 non-null float64				
	22 Analysis Neighborhoods dtypes: float64(10), int64(1) memory usage: 9.5+ MB  from sklearn.preprocessing in	34379 non-null float64 , object(12)	Scaler, Normali	izer		
	<pre>sc1 = MinMaxScaler() sc1_data = sc1.fit_transform plt.hist(data['inspection_scaler()</pre>					
	plt.show() 5000 -					
	3000 <b>-</b> 2000 <b>-</b>					
	1000 - 100	80 90 100				
10]:	plt.hist(sc1_data, 50) plt.show()					
	4000 -					
	2000 -					
	0.0 0.2 0.4	0.6 0.8 1.0				
	0.0 0.2 0.4  Масштабирование дан sc2 = StandardScaler()		енки - Stand	dardScaler¶		
12]:	plt.show()	(data[['inspection_score']])				
	4000 - 3500 - 3000 - 2500 -					
	2000 - 1500 - 1000 -					
13]:	$cat_{temp_data} = data[['busine]]$	ess_name']]				
13]:	<pre>cat_temp_data.head()  business_name  Cochinita #2</pre>					
	<ul><li>BREADBELLY</li><li>Great Gold Restaurant</li><li>HOMAGE</li></ul>					
14]:	# Импьютация наиболее частыме imp2 = SimpleImputer(missing	_values=np.nan, strategy='mo	st_frequent')			
14]:	<pre>data_imp2 = imp2.fit_transform data_imp2  array([['Cochinita #2'],</pre>					
15]:	<pre>['Philz Coffee'], ['El Gran Taco Loco'], ['Blue Bottle Coffee']  cat_enc = pd.DataFrame({'bus:</pre>	], dtype=object)				
15]:	cat_enc  business_name  Cochinita #2					
	<ul> <li>BREADBELLY</li> <li>Great Gold Restaurant</li> <li>HOMAGE</li> </ul>					
	<ul> <li>4 Pronto Pizza</li> <li></li> <li>53968 Blue Bottle Coffee</li> <li>53969 POKE KANA</li> </ul>					
	<ul> <li>53969 POKE KANA</li> <li>53970 Philz Coffee</li> <li>53971 El Gran Taco Loco</li> <li>53972 Blue Bottle Coffee</li> </ul>					
5	53973 rows × 1 columns	mport LabelEncoder OneWotte	coder			
ŀ	Кодирование категори  le = LabelEncoder()  cat_enc_le = le.fit_transform	ий целочисленными		и - label enco	ding	
	<pre>cat_enc['business_name'].unic array(['Cochinita #2', 'BREAD</pre>	que()				
19]:	<pre>np.unique(cat_enc_le) array([ 0,  1,  2,,</pre>	5569, 5570, 5571])				
20]:		RJUS', '111 Minna Gallery', s', '1428 Haight'], dtype=ob				
21]:	<b>Кодирование категори</b> ohe = OneHotEncoder()  cat_enc_ohe = ohe.fit_transfo			rı - one-hot ei	icuaing	
22]:	<pre>cat_enc.shape (53973, 1) cat_enc_ohe.shape</pre>					
23]: 24]:	(53973, 5572)  cat_enc_ohe					
25]:	<pre>cat_enc_ohe.todense()[0:10]</pre>	ments in Compressed Sparse R				
-2]:	matrix([[0., 0., 0.,, 0., [0., 0., 0.,, 0., [0., 0., 0.,, 0.,, 0., [0., 0., 0.,, 0., [0., 0., 0.,, 0., [0., 0., 0., 0.,, 0., [0., 0., 0., 0., 0.]]	<pre>0., 0.], 0., 0.],</pre>				
	[0., 0., 0.,, 0.,					
26]: 26]:	<ul><li>Cochinita #2</li><li>BREADBELLY</li><li>Great Gold Restaurant</li></ul>					
26]:	3 HOMAGE					
26]:	<ul><li>4 Pronto Pizza</li><li>5 Brickhouse</li></ul>					
26]:	<ul> <li>4 Pronto Pizza</li> <li>5 Brickhouse</li> <li>6 LAI HONG RESTAURANT</li> <li>7 Fools Errand</li> <li>8 MoBowL</li> </ul>					
26]:	<ul> <li>4 Pronto Pizza</li> <li>5 Brickhouse</li> <li>6 LAI HONG RESTAURANT</li> <li>7 Fools Errand</li> <li>8 MoBowL</li> </ul>					
26]: F 27]:	4 Pronto Pizza  5 Brickhouse  6 LAI HONG RESTAURANT  7 Fools Errand  8 MoBowL  9 CurveBall  Реализовываем "ящик с ус	_score'])				