In [1]:

import numpy as np import pandas as pd import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.preprocessing import LabelEncoder

In [3]:

df = pd.read_csv('D:\\Ботва\\Maгистратура\\2cem\\MMO\\PK\\Лосева\\winequality-red.cs df

Out[3]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide		density	рН	sulphates	alcohol
	0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
	1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
	2	7.8	0.760	0.04	2.3	NaN	15.0	54.0	0.9970	3.26	0.65	9.8
	3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
	4	7.4	0.700	0.00	1.9	NaN	11.0	34.0	0.9978	3.51	0.56	9.4
	5	7.4	0.660	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4
	6	7.9	0.600	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4
	7	7.3	0.650	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0
	8	7.8	0.580	0.02	2.0	NaN	9.0	18.0	0.9968	3.36	0.57	9.5
	9	7.5	0.500	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5
	10	6.7	0.580	0.08	1.8	0.097	15.0	65.0	0.9959	3.28	0.54	9.2
	11	7.5	0.500	0.36	6.1	NaN	17.0	102.0	0.9978	3.35	0.80	10.5
	12	5.6	0.615	0.00	1.6	0.089	16.0	59.0	0.9943	3.58	0.52	9.9
	13	7.8	0.610	0.29	1.6	0.114	9.0	29.0	0.9974	3.26	1.56	9.1
	14	8.9	0.620	0.18	3.8	0.176	52.0	145.0	0.9986	3.16	0.88	9.2
	15	8.9	0.620	0.19	3.9	0.170	51.0	148.0	0.9986	3.17	0.93	9.2
	16	8.5	0.280	0.56	1.8	0.092	35.0	103.0	0.9969	3.30	0.75	10.5
	17	8.1	0.560	0.28	1.7	0.368	16.0	56.0	0.9968	3.11	1.28	9.3
	18	7.4	0.590	0.08	4.4	NaN	6.0	29.0	0.9974	3.38	0.50	9.0
	19	7.9	0.320	0.51	1.8	0.341	17.0	56.0	0.9969	3.04	1.08	9.2
	20	8.9	0.220	0.48	1.8	0.077	29.0	60.0	0.9968	3.39	0.53	9.4
	21	7.6	0.390	0.31	2.3	0.082	23.0	71.0	0.9982	3.52	0.65	9.7
	22	7.9	0.430	0.21	1.6	0.106	10.0	37.0	0.9966	3.17	0.91	9.5
	23	8.5	0.490	0.11	2.3	NaN	9.0	67.0	0.9968	3.17	0.53	9.4
	24	6.9	0.400	0.14	2.4	0.085	21.0	40.0	0.9968	3.43	0.63	9.7
	25	6.3	0.390	0.16	1.4	NaN	11.0	23.0	0.9955	3.34	0.56	9.3
	26	7.6	0.410	0.24	1.8	0.080	4.0	11.0	0.9962	3.28	0.59	9.5
	27	7.9	0.430	0.21	1.6	0.106	10.0	37.0	0.9966	3.17	0.91	9.5

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
28	7.1	0.710	0.00	1.9	0.080	14.0	35.0	0.9972	3.47	0.55	9.4
29	7.8	0.645	0.00	2.0	NaN	8.0	16.0	0.9964	3.38	0.59	9.8
30	6.7	0.675	0.07	2.4	0.089	17.0	82.0	0.9958	3.35	0.54	10.1
31	6.9	0.685	0.00	2.5	0.105	22.0	37.0	0.9966	3.46	0.57	10.6
32	8.3	0.655	0.12	2.3	0.083	15.0	113.0	0.9966	3.17	0.66	9.8
33	6.9	0.605	0.12	10.7	0.073	40.0	83.0	0.9993	3.45	0.52	9.4
34	5.2	0.320	0.25	1.8	NaN	13.0	50.0	0.9957	3.38	0.55	9.2
35	7.8	0.645	0.00	5.5	0.086	5.0	18.0	0.9986	3.40	0.55	9.6
36	7.8	0.600	0.14	2.4	0.086	3.0	15.0	0.9975	3.42	0.60	10.8
37	8.1	0.380	0.28	2.1	NaN	13.0	30.0	0.9968	3.23	0.73	9.7
38	5.7	1.130	0.09	1.5	0.172	7.0	19.0	0.9940	3.50	0.48	9.8
39	7.3	0.450	0.36	5.9	0.074	12.0	87.0	0.9978	3.33	0.83	10.5
40	7.3	0.450	0.36	5.9	0.074	12.0	87.0	0.9978	3.33	0.83	10.5
41	8.8	0.610	0.30	2.8	0.088	17.0	46.0	0.9976	3.26	0.51	9.3
42	7.5	0.490	0.20	2.6	0.332	8.0	14.0	0.9968	3.21	0.90	10.5
43	8.1	0.660	0.22	2.2	0.069	9.0	23.0	0.9968	3.30	1.20	10.3
44	6.8	0.670	0.02	1.8	NaN	5.0	11.0	0.9962	3.48	0.52	9.5
45	4.6	0.520	0.15	2.1	0.054	8.0	65.0	0.9934	3.90	0.56	13.1
46	7.7	0.935	0.43	2.2	0.114	22.0	114.0	0.9970	3.25	0.73	9.2
47	8.7	0.290	0.52	1.6	0.113	12.0	37.0	0.9969	3.25	0.58	9.5
48	6.4	0.400	0.23	1.6	NaN	5.0	12.0	0.9958	3.34	0.56	9.2
49	5.6	0.310	0.37	1.4	0.074	12.0	96.0	0.9954	3.32	0.58	9.2
4											

In [4]:

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
#	COTUIIII	Non-Null Count	Drype
0	fixed acidity	50 non-null	float64
1	volatile acidity	50 non-null	float64
2	citric acid	50 non-null	float64
3	residual sugar	50 non-null	float64
4	chlorides	38 non-null	float64
5	free sulfur dioxide	50 non-null	float64
6	total sulfur dioxide	50 non-null	float64
7	density	50 non-null	float64
8	рН	50 non-null	float64
9	sulphates	50 non-null	float64
10	alcohol	50 non-null	float64
11	quality	50 non-null	int64

dtypes: float64(11), int64(1) memory usage: 4.8 KB In [13]: median h = df1['chlorides'].median() df1 = df.select_dtypes(include=[np.number]) df1['chlorides'] = df['chlorides'].fillna(median_h) In [14]: df1.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 50 entries, 0 to 49 Data columns (total 12 columns): # Column Non-Null Count Dtype -------fixed acidity 0 50 non-null float64 1 volatile acidity 50 non-null float64 citric acid 50 non-null float64 2 residual sugar 3 50 non-null float64 4 chlorides 50 non-null float64 5 free sulfur dioxide 50 non-null float64 total sulfur dioxide 50 non-null float64 6 7 50 non-null float64 density 8 50 non-null float64 рΗ 9 sulphates 50 non-null float64 10 alcohol 50 non-null float64 11 quality 50 non-null int64 dtypes: float64(11), int64(1) memory usage: 4.8 KB In [15]: min = np.percentile(df1.sulphates, 5) max = np.percentile(df1.sulphates, 95) print(min, max) 0.489 1.1459999999999997 In [16]: df1[(df1.sulphates < min)] = min</pre> df1[(df1.sulphates > max)] = max In [17]: df1 Out[17]: free total fixed volatile citric residual

	acidity	acidity	acid	sugar	chlorides	sulfur dioxide	sulfur dioxide	density	рН	sulphates	alcohol
0	7.400	0.700	0.000	1.900	0.076	11.000	34.000	0.9978	3.510	0.560	9.400
1	7.800	0.880	0.000	2.600	0.098	25.000	67.000	0.9968	3.200	0.680	9.800
2	7.800	0.760	0.040	2.300	0.086	15.000	54.000	0.9970	3.260	0.650	9.800
3	11.200	0.280	0.560	1.900	0.075	17.000	60.000	0.9980	3.160	0.580	9.800
4	7.400	0.700	0.000	1.900	0.086	11.000	34.000	0.9978	3.510	0.560	9.400
5	7.400	0.660	0.000	1.800	0.075	13.000	40.000	0.9978	3.510	0.560	9.400
6	0.489	0.489	0.489	0.489	0.489	0.489	0.489	0.4890	0.489	0.489	0.489
7	0.489	0.489	0.489	0.489	0.489	0.489	0.489	0.4890	0.489	0.489	0.489
8	7.800	0.580	0.020	2.000	0.086	9.000	18.000	0.9968	3.360	0.570	9.500
9	7.500	0.500	0.360	6.100	0.071	17.000	102.000	0.9978	3.350	0.800	10.500

	MMO RK1										
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
10	6.700	0.580	0.080	1.800	0.097	15.000	65.000	0.9959	3.280	0.540	9.200
11	7.500	0.500	0.360	6.100	0.086	17.000	102.000	0.9978	3.350	0.800	10.500
12	5.600	0.615	0.000	1.600	0.089	16.000	59.000	0.9943	3.580	0.520	9.900
13	1.146	1.146	1.146	1.146	1.146	1.146	1.146	1.1460	1.146	1.146	1.146
14	8.900	0.620	0.180	3.800	0.176	52.000	145.000	0.9986	3.160	0.880	9.200
15	8.900	0.620	0.190	3.900	0.170	51.000	148.000	0.9986	3.170	0.930	9.200
16	8.500	0.280	0.560	1.800	0.092	35.000	103.000	0.9969	3.300	0.750	10.500
17	1.146	1.146	1.146	1.146	1.146	1.146	1.146	1.1460	1.146	1.146	1.146
18	7.400	0.590	0.080	4.400	0.086	6.000	29.000	0.9974	3.380	0.500	9.000
19	7.900	0.320	0.510	1.800	0.341	17.000	56.000	0.9969	3.040	1.080	9.200
20	8.900	0.220	0.480	1.800	0.077	29.000	60.000	0.9968	3.390	0.530	9.400
21	7.600	0.390	0.310	2.300	0.082	23.000	71.000	0.9982	3.520	0.650	9.700
22	7.900	0.430	0.210	1.600	0.106	10.000	37.000	0.9966	3.170	0.910	9.500
23	8.500	0.490	0.110	2.300	0.086	9.000	67.000	0.9968	3.170	0.530	9.400
24	6.900	0.400	0.140	2.400	0.085	21.000	40.000	0.9968	3.430	0.630	9.700
25	6.300	0.390	0.160	1.400	0.086	11.000	23.000	0.9955	3.340	0.560	9.300
26	7.600	0.410	0.240	1.800	0.080	4.000	11.000	0.9962	3.280	0.590	9.500
27	7.900	0.430	0.210	1.600	0.106	10.000	37.000	0.9966	3.170	0.910	9.500
28	7.100	0.710	0.000	1.900	0.080	14.000	35.000	0.9972	3.470	0.550	9.400
29	7.800	0.645	0.000	2.000	0.086	8.000	16.000	0.9964	3.380	0.590	9.800
30	6.700	0.675	0.070	2.400	0.089	17.000	82.000	0.9958	3.350	0.540	10.100
31	6.900	0.685	0.000	2.500	0.105	22.000	37.000	0.9966	3.460	0.570	10.600
32	8.300	0.655	0.120	2.300	0.083	15.000	113.000	0.9966	3.170	0.660	9.800
33	6.900	0.605	0.120	10.700	0.073	40.000	83.000	0.9993	3.450	0.520	9.400
34	5.200	0.320	0.250	1.800	0.086	13.000	50.000	0.9957	3.380	0.550	9.200
35	7.800	0.645	0.000	5.500	0.086	5.000	18.000	0.9986	3.400	0.550	9.600
36	7.800	0.600	0.140	2.400	0.086	3.000	15.000	0.9975	3.420	0.600	10.800
37	8.100	0.380	0.280	2.100	0.086	13.000	30.000	0.9968	3.230	0.730	9.700
38	0.489	0.489	0.489	0.489	0.489	0.489	0.489	0.4890	0.489	0.489	0.489
39	7.300	0.450	0.360	5.900	0.074	12.000	87.000	0.9978	3.330	0.830	10.500
40	7.300	0.450	0.360	5.900	0.074	12.000	87.000	0.9978	3.330	0.830	10.500
41	8.800	0.610	0.300	2.800	0.088	17.000	46.000	0.9976	3.260	0.510	9.300
42	7.500	0.490	0.200	2.600	0.332	8.000	14.000	0.9968	3.210	0.900	10.500
43	1.146	1.146	1.146	1.146	1.146	1.146	1.146	1.1460	1.146	1.146	1.146
44	6.800	0.670	0.020	1.800	0.086	5.000	11.000	0.9962	3.480	0.520	9.500

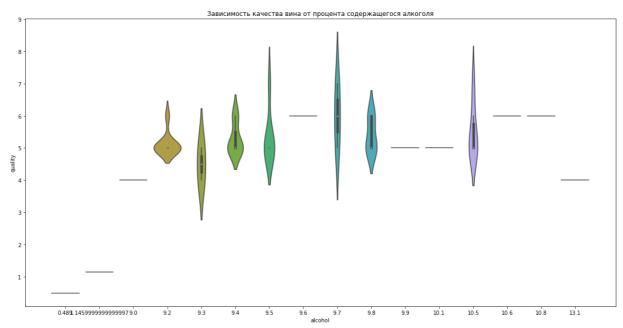
		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
-	45	4.600	0.520	0.150	2.100	0.054	8.000	65.000	0.9934	3.900	0.560	13.100
	46	7.700	0.935	0.430	2.200	0.114	22.000	114.000	0.9970	3.250	0.730	9.200
	47	8.700	0.290	0.520	1.600	0.113	12.000	37.000	0.9969	3.250	0.580	9.500
	48	6.400	0.400	0.230	1.600	0.086	5.000	12.000	0.9958	3.340	0.560	9.200
	49	5.600	0.310	0.370	1.400	0.074	12.000	96.000	0.9954	3.320	0.580	9.200

In [87]:

```
plt.figure(figsize=(20, 10))
ax = sns.violinplot(df1.alcohol, df1.quality)
ax.set(xlabel='alcohol', ylabel='quality', title='Зависимость качества вина от проце
plt.plot()
```

c:\users\sveta\documents\virtualenvs\tensorflow\lib\site-packages\seaborn_decorator
s.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From ver
sion 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
FutureWarning

Out[87]: []



In []: