import numpy as np import pandas as pd import seaborn as sns import matplotlib.pyplot as plt from sklearn.linear_model import LinearRegression from sklearn import metrics In [2]: data=pd.read_csv("WQ.csv") In [3]: data.head() Out[3]: fixed acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide
2 7.8 0.76 0.04 2.3 0.092 15.0 54.0 0.970 3.26 0.65 9.8 5 3 11.2 0.28 0.56 1.9 0.075 17.0 60 0 0.9980 3.16 0.58 9.8 6 4 7.4 0.70 0.00 1.9 0.076 11.0 34.0 0.9978 3.5 0.56 9.4 5 In [4]: data tail() Tixed acidity volatile acidity cliric acid residual sugar cliorides free sulfur dioxide displayed acidity signal free sulfur dioxide dioxide
The color Section Color
Solution Color C
dtypes: float64(11), int64(1) memory usage: 150.0 KB In [7]: data.columns Out[7]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
700
Out[11]: data['alcohol'].describe() Out[11]: count
50% 2.260000 75% 2.600000 max 15.5500000 Name: residual sugar, dtype: float64 In [13]: q1= data.quantile(0.25) q2= data.quantile(0.75) IQR=q2-q1 print(IQR) fixed acidity 0.250000 citric acid 0.330000 residual sugar 0.7000000 clivides 0.020000 free sulfur dioxide 14.000000 total sulfur dioxide 40.000000 density 0.602235
PH
False False False False False False False
4 False False
TypeError: unsupported operand type(s) for : 'NoneType' and 'bool' During handling of the above exception, another exception occurred: ValueError
<pre>~\anaconda3\lib\site-packages\pandas\core\ops\common.py in new_method(self, other) 67</pre>
<pre>~\anaconda3\lib\site-packages\pandas\core\frame.py in _dispatch_frame_op(self, right, func, axis) 6891</pre>
> 381
In [18]: data_out_data[-((data<(q1 - 1.5*IQR))] (data>(q2+1.5*IQR))).any(axis=1)] Out[18]: (1179, 12) In [19]: data_out In [19]:
1594 6.2 0.600 0.08 2.0 0.090 32.0 44.0 0.9940 3.45 0.58 10.5 5 1595 5.9 0.550 0.10 2.2 0.062 39.0 51.0 0.99512 3.52 0.76 11.2 6 1596 6.3 0.510 0.13 2.3 0.076 29.0 40.0 0.9954 3.42 0.75 11.0 6 1597 5.9 0.645 0.12 2.0 0.075 32.0 44.0 0.9954 3.57 0.71 10.2 5 1598 6.0 0.310 0.47 3.6 0.067 18.0 42.0 0.99549 3.9 0.66 11.0 6 1179 rows × 12 columns
fixed acidity-volatile acidity-citric acid residual sugar-citric acid resid
In [22]: correlation.sort_values(ascending=False) Out[22]: alcohol
abs_corrs=correlation.abs() high_correlations= abs_corrs[abs_corrs> correlation_threshold].index.values.tolist() return high_correlations In [31]: feature= features(0.05) print(feature) x=data_out[feature] y=data_out['quality'] ['fixed acidity', 'volatile acidity', 'citric acid', 'chlorides', 'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol'] In [33]: bx=sns.boxplot(x='quality',y='alcohol',data=data) bx.set(xlabel='quality',y abel='alcohol',title='alcohol % in different samples') Out[33]: [Text(0.5, 0, 'quality'), Text(0, 0.5, 'alcohol'), Text(0.5, 1.0, 'alcohol % in different samples')]
In [34]: bx=sns.boxplot(x='quality',y='fixed acidity',data=data) bx.set(Xlabel='quality',ylabel='fixed acidity',title='fixed acidity', in different samples')
Out[34]: [Text(0.5, 0, 'quality'), Text(0.5, 1.0, 'fixed acidity'), Text(0.5, 1.0, 'fixed acidity % in different samples')] fixed acidity % in different samples 10
Th [35]:
1596 6.3 0.510 0.13 0.076 40.0 0.99574 3.42 0.75 11.0 1597 5.9 0.645 0.12 0.075 44.0 0.99547 3.57 0.71 10.2 1598 6.0 0.310 0.47 0.067 42.0 0.99549 3.39 0.66 11.0 1179 rows × 9 columns In [36]: y Out [36]: 0 5 2 5 3 6 4 5 1594 5 1595 6 1596 6
1597 5 1598 6 Name: quality, Length: 1179, dtype: int64 In [42]: from sklearn.model_selection import train_test_split x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=2) In [44]: y_test.shape Out[44]: (236,) In [46]: regression=LinearRegression() regression.fit(x_train,y_train) Out[46]: LinearRegression()
In [47]: regression.intercept
5.36820934, 5.49217966, 5.92323014, 5.2006576, 5.84617714, 6.18275713, 5.09410179, 5.1930855, 5.68380962, 5.68746015, 5.60001224, 5.59512978, 5.10291123, 5.70000066, 4.94025416, 5.44889762, 5.94224609, 4.94107609, 6.181582, 5.57255281, 5.6237674, 5.09647769, 5.49635084, 5.6170322, 5.01108618, 5.76908122, 5.5324864, 5.81370556, 5.11236736, 6.64381026, 6.6658669, 4.99789961, 5.4925294, 5.73881207, 5.06544651, 5.85290174, 5.82813979, 5.40693088, 5.75808852, 5.47463217, 6.44249023, 5.27590399, 5.4349732, 6.02515073, 5.97210664, 5.62668206, 5.46050703, 5.79991585, 5.05104314, 5.48084207, 5.14483778, 5.38251507, 6.21676455, 5.02289511, 6.11069795, 5.55527286, 5.30799387, 5.59670949, 5.35949131, 5.2130437, 5.04183542, 5.54464829, 5.49558467, 5.08372451, 5.3989288, 5.97931, 5.92064592, 6.35640918, 6.12339444, 5.22167564, 5.41875837, 4.89786513, 6.22876541, 6.25512769, 5.60243001, 5.12983458, 5.76818237, 5.58670197, 5.76069934, 5.61081705, 5.5266676, 6.33447057, 5.084158, 5.328881, 5.55231876, 5.76166446, 6.1511302, 5.61948116, 5.46074367, 5.57005355, 5.61691253, 5.35274099, 5.0352097, 5.56248262, 5.71242758,
5.93478454, 5.03777322, 5.26682364, 5.64953808, 6.39986833, 5.75808852, 5.1128198, 5.17775114, 5.1775114, 5.38099485, 5.42630268, 6.19072202, 6.2817073, 5.34271711, 5.88099485, 5.42630268, 6.37018646, 5.93883091, 6.23793031, 5.32261901, 5.56284321, 5.30032349, 6.08215011, 6.15473121, 6.5734642, 5.08823729, 5.129938, 5.30072078, 6.05449014, 5.2679647, 5.39082489, 5.19356026, 5.90748173, 5.46572757, 6.05877138, 6.38942355, 5.10317545, 5.49828333, 5.09647769, 5.12361348, 5.55383885, 6.0100637, 5.80913109, 5.36392387, 5.63274594, 5.71758241, 6.50303734, 5.39470266, 5.62602085, 5.25302853, 5.25479934, 5.10354633, 5.05298109, 6.63101459, 5.63295259, 5.49320316, 6.29457261, 4.85142777, 4.97016389, 5.2361203, 5.78310152, 5.59670949, 5.58709219, 5.43864459, 4.96491159, 6.38214582, 5.7521515, 5.30568176, 5.3095585, 5.70290237, 5.21075232, 5.33212684, 5.24217643, 5.0952589, 5.62182834, 6.42059204, 5.17293625, 6.49528566, 5.4467208, 5.4502697, 5.2853643, 5.71758241, 5.30628657, 5.52860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12860705, 5.12836043, 5.71758241, 5.30028657, 5.622860705, 5.11833662, 4.94071576,
5.85341474, 5.05972904, 5.72160972, 5.20808612, 5.85081915, 5.54988899, 5.1167663, 6.63321452, 6.56094944, 5.7727045, 5.38294361, 5.23412709, 5.41018534, 5.38876987, 5.7521515, 5.01098515, 5.51194249, 5.48492275, 5.28533643, 6.52570903, 5.19951764, 5.54035019, 5.08932006, 6.35040918, 6.78026311, 5.46132363, 5.67512976, 5.6835253, 5.54102276, 4.884702, 5.13616426, 5.37069164, 5.17175114, 5.54436402, 5.56660361, 5.36571536, 5.59967106, 5.17775114, 5.54436402, 5.56660361, 5.36571536, 5.23376521, 5.57425087, 6.14318226, 5.38350434, 5.93326312, 6.16789129, 6.13300161, 5.08643449, 6.72408319, 6.59999706, 5.38121505, 5.97636239, 6.07441946, 5.09268074, 6.18557109, 5.2645153, 5.20653806, 5.59966919, 5.7585275, 5.76841884, 6.35576195, 5.09647769, 6.31572278, 5.69461175, 5.47204517, 5.17906841, 4.79491614, 5.2798985, 5.0229152, 5.37533452, 5.47421137, 5.39683163, 5.99824082, 5.07108137, 5.22938007, 5.03797701, 5.50741182, 6.2302486, 5.06647694, 6.20769442, 4.99459713, 5.08498047, 5.00615388, 5.6638447, 6.50769442, 4.99459713, 5.08498047, 5.00615388, 5.6638447, 6.507695442, 5.21862348, 5.32059966, 5.44314028, 5.06618498, 6.33383182, 5.21862348, 5.32059966, 5.44314028, 5.06618498, 6.33383182, 5.32797603, 5.34648252, 5.73118915, 5.07288293, 6.2195839, 5.86346566, 5.30239928, 7.00729984, 5.77527045, 5.24391703,
5.51883865, 5.3034184, 6.15625802, 5.43378405, 6.18273086, 5.86452364, 5.1810682, 5.85974408, 4.9385522, 5.5569301, 5.14962165, 5.61142897, 6.4611083, 5.63162616, 5.23376521, 5.18674976, 6.08742828, 5.48619797, 6.21962785, 5.49828333, 5.62787409, 5.94648596, 5.9658969, 5.33955262, 5.24507359, 5.69873269, 6.53188067, 5.38362903, 5.47939272, 5.86410748, 6.09948668, 5.26813794, 6.41984292, 5.39897165, 5.35654621, 6.32493852, 5.99511272, 5.69830359, 5.40194533, 5.60900722, 5.52144259, 6.42142059, 5.63264204, 5.12602326, 5.48938499, 5.21617861, 6.69186847, 5.41081511, 5.55046081, 5.5685828, 5.99946612, 5.99914371, 5.39218743, 5.37337766, 6.47547623, 6.02767314, 5.79201567, 5.85341474, 5.71600685, 6.21584025, 5.77759777, 6.36496074, 5.57663277, 5.20274492, 4.93517947, 5.98287109, 5.54095781, 6.04729853, 5.26614098, 5.35274099, 5.18280788, 5.33463092, 5.72153206, 5.57409265, 5.25730919, 5.11218198, 5.54117015, 5.86081352, 5.3268841, 5.101553, 5.49175761, 5.38563366, 6.25512769, 5.82462713, 5.48945164, 6.3336996, 6.27574578, 6.185732311, 5.3416769, 5.73118915, 6.4492386, 4.90797991, 5.27076942, 5.28447672, 5.20771977,
5.63222254, 5.03673015, 6.14355968, 6.52632161, 5.09215159, 5.4229847, 5.41750294, 5.47768294, 5.470862943, 5.31096715, 5.75600385, 5.35145348, 5.03491847, 5.36484881, 5.36706206, 5.56022865, 5.85942364, 6.06333416, 6.23818238, 5.5576522, 5.91625729, 5.85382361, 5.00217317, 5.41573407, 6.10079643, 5.54545059, 5.47453626, 5.32150363, 5.10619683, 5.13689588, 5.6170322, 6.09440998, 5.62626975, 5.11563441, 4.91925904, 5.92114478, 6.07983349, 5.70000066, 5.13165446, 6.29003133, 5.17865042, 5.22574315, 5.94603721, 5.05029534, 5.46464617, 6.45657259, 5.94027897, 5.50916455, 5.70484926, 6.07338725, 5.26709647, 5.78349718, 5.42134958, 4.97167404, 5.43378405, 5.82797532, 5.39322356, 6.121393998, 5.8694658, 5.21403313, 6.5734642, 5.40058712, 5.95420685, 5.46661876, 6.07312268, 5.65562488, 5.24347637, 5.39766905, 5.87933442, 5.5935613, 5.17959089, 5.72057504, 6.1991190, 5.43240124, 5.7350634, 5.40077999, 5.37422177, 6.05717439, 5.34447523, 5.13318932, 5.11499999, 5.19856301, 5.221675644, 5.15930339, 6.33129382, 5.100801278, 5.0568108, 5.94787774, 6.53386046, 6.331243852, 4.84507443, 5.48619797, 5.80186036, 5.40637433, 5.68995625, 5.59507948, 5.06541651, 5.41487779, 4.7249645, 5.25435658, 5.59507948, 5.06541651, 5.41487779, 4.7249645, 5.25435658,
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5.50955655, 5.2703363 , 5.6961587 , 5.2581744 , 5.65462698, 5.47251363 , 5.23825846 , 5.23873638 , 5.68512199 , 5.4070197 , 5.68995625, 6.27692182, 6.163134 , 5.52404369 , 5.47822543, 5.54568711, 5.56243588, 6.56735218, 6.56646063, 5.17293625, 5.77752669, 5.14824165, 5.20604932, 5.65952075, 5.50353636, 5.06409375, 6.04914359 , 4.84106642, 5.36644261, 5.101553 , 5.67108966, 5.14483778, 6.15869422, 5.16547531, 5.54754074, 5.50714665, 5.49217966, 5.3736946 , 6.33383182, 5.06530238, 5.24499396, 5.53686473, 5.55745727, 5.76892405, 5.80026999, 6.25648233, 6.20753015, 4.9924918, 6.26822657, 6.50303734, 5.59996582, 6.09766492, 5.37989418, 6.56630238, 5.33435873, 5.87312264, 5.48663622, 5.7489395, 4.98759902, 6.24437148, 6.58995156, 4.93830717, 5.21529197, 5.00244584, 5.37766168, 6.15567245, 6.06309838, 5.1946648, 5.72184938, 5.53917936, 5.25936283, 5.25736919, 5.47579108, 6.15567245, 5.23204351, 5.30239928, 5.28335425, 6.03861458, 5.7508508, 5.5299978, 5.3663345, 5.88489996, 5.0275512, 5.3511309, 6.30177007, 6.33336996, 5.48198848, 5.87294728, 5.56014018, 5.12580074, 5.0318976, 5.08800544, 5.4679416, 5.90271527, 5.3154221, 5.12654747, 6.29414372, 6.15991688, 5.59818891,
6.29601829, 5.09248003, 6.1300031 , 5.18965152, 5.4349732 , 5.58631046, 5.58709219, 5.77305472, 5.13332863, 5.06329732, 6.20411808, 5.68746015, 5.98696397, 5.61163635, 6.06629853, 5.21774798, 5.20258581, 5.05495973, 5.87369086, 5.58778496, 5.77084712, 6.307712 , 5.88199025, 6.31095042, 5.74441465, 5.40357843, 5.09599607, 6.41443265, 5.78892634, 5.97512025, 5.14962165, 6.16362365, 5.7820873, 6.42848296, 6.02515073, 6.71785664, 5.85290174, 6.15653378, 6.10982543, 5.39393368, 5.80485599, 5.93876605, 4.8633533, 5.95426304, 6.08819316, 5.23204351, 6.30957888, 5.565757 , 5.21825697, 4.92310645, 6.15991688, 5.8580258 , 5.62787409, 5.37401695, 6.4067045 , 6.28901085, 5.28349085, 5.23885629, 5.21970606, 5.07806046, 5.29678052, 5.15833623, 5.2398277, 5.20390975, 4.78661624, 6.14670094, 5.97636239, 5.88470611, 6.23299083, 5.03610653, 5.76447027, 5.56857234, 5.51909511, 5.61618419, 5.82015356, 5.76447027, 5.56857234, 5.51909511, 5.61618419, 5.82015356, 5.74441665, 5.95804421, 5.37214771, 5.55690525, 5.6823556, 5.3086708, 5.53128695, 5.59781054, 5.21756925, 5.64087984, 5.1274077,
4.84100642, 5.64901139, 6.18892256, 6.15472394, 6.40297502, 5.0323977, 5.48492275, 5.26813794, 5.31868162, 5.3661849, 5.46074367, 6.0100637, 5.9796431, 5.38691885, 6.07105301, 4.91053182, 6.19072202, 5.92064592, 6.41493553, 5.9860093, 5.96240259, 5.68973263, 5.689733537, 6.20760998, 5.75812996, 6.11882856, 5.30332594, 6.62270262, 6.38798739, 5.46332282, 5.56619161, 6.53188067, 5.18647495, 5.71242758, 5.44509131, 5.40094065, 5.20645014, 5.15849111]) In [50]: test_pred=regression.predict(x_test) test_pred Out[50]: array([5.61948116, 5.15676143, 5.35463723, 5.87369086, 5.41906975, 6.19248853, 5.74035291, 5.64727915, 5.98671473, 6.00072399, 5.27454777, 5.40945434, 5.57676647, 5.57838617, 5.45287962, 5.9298555, 5.30334908, 5.917136, 5.22335787, 5.45272283, 5.22298198, 5.808186036, 5.8708036, 5.37242241, 5.20884814, 5.69829008, 5.91933139, 5.50964271, 5.2742391, 5.18914673, 5.73773759, 6.15823912, 5.33843571, 5.94245806, 5.19951764, 5.35949131, 6.02743914, 5.28680258, 5.77153256, 5.39951764, 5.35949131, 6.02743914, 5.28680258, 5.77153256, 5.39951764, 5.35949131, 6.02743914, 5.28680258, 5.77153256, 5.36644261,
5.59386133, 5.87189867, 5.41081511, 5.2656031, 5.143201, 5.56873032, 5.02663018, 5.86410748, 5.93883901, 5.65200469, 5.37837239, 6.275748748, 5.49865162, 5.5188083, 5.36706206, 5.80936033, 5.69829008, 5.9635673, 5.2148181, 5.40225228, 5.00599636, 6.23299083, 5.19099644, 4.97051039, 5.67512976, 5.3308828, 5.32298492, 6.73751649, 5.14000912, 4.66001182, 5.99511008, 5.75344256, 5.55441525, 4.99722638, 5.2580626, 5.47086312, 5.30546346, 5.20106422, 5.29261872, 5.38272235, 5.30485161, 5.26000016, 5.90271527, 5.09848534, 6.00727672, 5.59060136, 5.22941222, 5.57441106, 5.61163635, 6.4635574, 5.02459147, 6.32527157, 6.13097115, 6.47640016, 5.30032349, 5.22334124, 5.98636391, 5.12878767, 5.87131644, 5.20390075, 6.38942355, 5.35984636, 5.26807669, 4.98279895, 5.47822543, 5.14562594, 6.44812666, 6.69018458, 5.03610653, 5.52275875, 5.73897817, 5.1568226, 5.60552579, 5.17380791, 5.82797532, 5.82257746, 6.6499719, 5.0385866, 5.76575417, 6.081939394, 5.88709219, 5.29443058, 5.82462713, 5.45958046, 5.16624952, 5.6327017, 5.99356431, 5.54707273, 5.76657853, 5.065672429, 5.48819888, 6.16055292, 5.57102546, 5.40382215, 6.21584025, 5.48819888, 6.16055292, 5.57102546, 5.40382215, 6.21584025,
5.93120481, 5.23665437, 5.91067653, 5.1810682, 5.84909792, 5.808783531, 6.0263082, 5.86981453, 5.0831891, 5.46064463, 5.82630789, 5.42634765, 5.2488097, 5.4240555, 5.407800113, 6.34651266, 5.38138031, 5.047408018, 5.8324454, 6.26648296, 6.3417819, 5.51302518, 5.09741095, 6.27579257, 5.2486789, 5.31421043, 6.42142059, 6.07204285, 5.86576571, 6.04284948, 4.97966776, 5.92736963, 6.19072202, 5.20465451, 5.29130437, 5.26000016, 5.86834102, 5.706161938, 5.73618272, 5.75600385, 5.0615388, 5.34447523, 6.20260509, 5.02487099, 5.37147281, 5.5900819, 5.36488282, 5.8314728, 5.09268074, 5.49175761, 5.26000016, 6.00124977, 5.75081725, 5.49164003, 5.86372445, 5.37978529, 5.88099485, 6.49990095, 5.21825607, 6.19041585, 5.28447672, 6.05414271, 5.40127984, 6.09462497, 5.4860314, 5.491761, 5.8823848, 6.0092074, 5.81187172, 5.54870198, 5.7431205, 5.09848534, 5.3482848, 6.09462974, 5.4817678, 6.946497, 5.48200469, 5.07883842, 5.73221695, 5.98636331, 6.13439934, 6.34577646, 5.17111584, 5.88020393, 6.20985732, 5.2668626, 5.11427755, 5.06166028, 5.19768039, 5.29854314, 5.55200469, 5.17111584, 5.88020393, 6.20985732, 5.266866, 5.11427755, 5.06166028, 5.19768039, 5.8956314, 6.39795733, 5.12263143, 5.14515066, 5.98671473, 5.36615344, 5.40225228, 5.05672429, 6.627439141)
6.02743914]) In [51]: train_rms= metrics.mean_squared_error(train_pred, y_train)**0.5 train_rms
Out[51]: 0.5724464562781634 In [53]: train_rms= metrics.mean_squared_error(test_pred, y_test)**0.5 train_rms Out[53]: 0.5609706590975136 In [54]: predictData= np.round_(test_pred) predictData Out[54]: array([6., 5., 5., 6., 6., 6., 6., 6., 6., 5., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 5., 6., 6., 5., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 6., 6., 5., 5., 5., 5., 5., 5., 5., 5., 5., 5
In [53]: train_rms= metrics.mean_squared_error(test_pred, y_test)**0.5 train_rms Out[53]: 0.5609706590975136 In [54]: predictbata= np.round_(test_pred) predictbata Out[54]: array([8., 5., 5., 6., 6., 5., 6., 6., 5., 5., 6., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 6., 6., 5., 5., 5., 5., 5., 5., 5., 5., 5., 5
Trail_ms refiscation and appared_error(test_pred, y_test)**0.5
De 1811 Frank press merties mean _squared_errar(test_prec, v_loss)*18.5
10 103
Train (For Secretic Analyses (Contest Large Contest Large