

# quiz1

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Submitted by: Fawad Kirmani

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```
[1]: import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
import matplotlib.pyplot as plt
import seaborn as sns
```

**Task 1 – Load data programmatically (10 points), summarize its statistics (10 points) and report on missing data (10 points). Note that a number of parameters are reported for the same date/time in successive rows. Load data**

```
[2]: input_data = pd.read_csv('./data/WaterAtlas-OneLake.csv')
input_data.head()
```

```
[2]:   WBodyID      WaterBodyName  DataSource StationID StationName \
0   2003889  Okaloacoochee Branch  WIN_21FLSFWM      32275      CRFW09
1   2003889  Okaloacoochee Branch  WIN_21FLSFWM      32275      CRFW09
2   2003889  Okaloacoochee Branch  WIN_21FLSFWM      32275      CRFW09
3   2003889  Okaloacoochee Branch  WIN_21FLSFWM      32275      CRFW09
4   2003889  Okaloacoochee Branch  WIN_21FLSFWM      32275      CRFW09
```

```
   Actual_StationID  Actual_Latitude  Actual_Longitude  DEP_WBID \
0                32275           26.7629           -81.4001    32350
1                32275           26.7629           -81.4001    32350
2                32275           26.7629           -81.4001    32350
3                32275           26.7629           -81.4001    32350
4                32275           26.7629           -81.4001    32350
```

```
   SampleDate  ...  DepthUnits  Parameter \
0  5/18/2020 11:11:00 AM  ...      m    TN_ugl
1  5/18/2020 11:11:00 AM  ...      m  NH3_N_ugl
2  5/18/2020 11:11:00 AM  ...      m   NOx_ugl
3  5/18/2020 11:11:00 AM  ...      m    TP_ugl
4  5/18/2020 11:11:00 AM  ...      m   OP_mgl
```

	Characteristic	Sample_Fraction	Result_Value \
0	Nitrogen	Total	1280.000
1	Nitrogen, ammonia as N	Dissolved	203.000
2	Nitrogen, Nitrite (NO2) + Nitrate (NO3) as N	Dissolved	9.000
3	Phosphorus as P	Total	52.000
4	Phosphorus, phosphate (PO4) as P	Dissolved	0.002

	Result_Unit	QACode	Result_Comment	Original_Result_Value \
0	ug/l	NaN	NaN	1.280
1	ug/l	NaN	NaN	0.203
2	ug/l	I	NaN	0.009
3	ug/l	NaN	NaN	0.052
4	mg/l	I	NaN	0.002

	Original_Result_Unit
0	mg/L
1	mg/L
2	mg/L
3	mg/L
4	mg/L

[5 rows x 21 columns]

As data is for single lake, removing "WBodyID", "WaterBodyName", "DataSource", "StationID", "StationName", "Actual\_StationID", "Actual\_Latitude", "Actual\_Longitude", "DEP\_WBID".

Also not including for data exploration: "Sample\_Fraction", "ActivityDepth", "DepthUnits", "QA-Code", "Original\_Result\_Comment", "Characteristic", "Original\_Result\_Unit", "Result\_Unit".

Excluding Original\_Result\_Value and including Result\_Value as Result\_Value are updated units.

```
[3]: input_data_pivot = input_data.pivot_table(columns="Parameter",
        index=["SampleDate", "ActivityDepth"],
        values="Result_Value").reset_index()

input_data_pivot
```

[3]:	Parameter	SampleDate	ActivityDepth	24D_ugl	Ag_ugl	Al_ugl \
0		01-11-1978 0:00	0.500000	NaN	NaN	NaN
1		01-11-2021 12:08	0.410000	NaN	NaN	NaN
2		02-08-1978 0:00	0.500000	NaN	NaN	NaN
3		02-08-2021 11:06	0.500000	NaN	NaN	NaN
4		02-12-1979 0:00	0.500000	NaN	NaN	NaN
..		...	...	...	...	...
98	9/13/1978 12:00:00 AM		0.500000	NaN	NaN	NaN
99	9/16/1980 12:00:00 AM		0.500000	NaN	NaN	NaN
100	9/19/2013 12:00:00 AM		0.152439	NaN	NaN	NaN
101	9/20/2016 12:00:00 AM		0.300000	NaN	NaN	NaN
102	9/21/2020 11:43:00 AM		0.500000	NaN	NaN	NaN

Parameter	Alk_CaCO3_mgl	As_ugl	BOD5_mgl	B_ugl	Ba_ugl	...	TN_ugl	\
0	243.0	NaN	NaN	NaN	NaN	...	464.0	
1	NaN	NaN	NaN	NaN	NaN	...	987.0	
2	263.5	NaN	NaN	NaN	NaN	...	1301.0	
3	NaN	NaN	NaN	NaN	NaN	...	879.0	
4	NaN	NaN	NaN	NaN	NaN	...	NaN	
..	...	...	...	...	...	...		
98	221.0	NaN	NaN	NaN	NaN	...	978.0	
99	NaN	NaN	NaN	NaN	NaN	...	1660.0	
100	NaN	NaN	NaN	NaN	NaN	...	NaN	
101	NaN	1.78	NaN	NaN	NaN	...	1210.0	
102	NaN	NaN	NaN	NaN	NaN	...	1470.0	

Parameter	TOC_mgl	TP_ugl	TSS_mgl	TempW_C	TempW_F	Tl_ugl	Turb_ntu	\
0	NaN	20.0	NaN	16.70	62.060	NaN	NaN	
1	NaN	48.0	NaN	19.30	66.740	NaN	NaN	
2	NaN	14.5	NaN	15.90	60.620	NaN	NaN	
3	NaN	43.0	NaN	20.80	69.440	NaN	NaN	
4	NaN	28.5	NaN	16.20	61.160	NaN	NaN	
..	...	...	...	...	...	...		
98	NaN	26.5	NaN	29.70	85.460	NaN	NaN	
99	NaN	131.0	NaN	27.60	81.680	NaN	NaN	
100	NaN	NaN	NaN	27.26	81.068	NaN	NaN	
101	22.0	170.0	6.0	28.00	82.400	NaN	3.5	
102	NaN	264.0	NaN	28.80	83.840	NaN	NaN	

Parameter	Zn_ugl	pH
0	NaN	7.720
1	NaN	7.900
2	NaN	7.610
3	NaN	8.100
4	NaN	7.220
..	...	...
98	NaN	7.500
99	NaN	7.230
100	NaN	7.445
101	NaN	7.200
102	NaN	7.500

[103 rows x 74 columns]

```
[4]: input_data_pivot.rename(columns={'Sucralose_ug/l': 'Sucralose_ugl'},  
    ↪ inplace=True)
```

summarizing statistics of input\_data\_pivot dataframe

```
[5]: summary = input_data_pivot.describe()
print(summary.columns)
summary
```

```
Index(['ActivityDepth', '24D_ugl', 'Ag_ugl', 'Al_ugl', 'Alk_CaCO3_mgl',
      'As_ugl', 'BOD5_mgl', 'B_ugl', 'Ba_ugl', 'C_organic_mgl', 'Ca_diss_mgl',
      'Ca_mgl', 'CarbAlk_mgl', 'Cd_ugl', 'ChlaC_ugl', 'Chla_ugl',
      'Cl_diss_mgl', 'Cl_mgl', 'Color_true_pcu', 'Cond_umhocm', 'Cr_ugl',
      'Cu_diss_ugl', 'Cu_ugl', 'DO_mgl', 'DO_percent', 'Depth_bott_ft',
      'Diuron_ugl', 'Ecoli_100ml', 'Endothall_ugl', 'F_mgl', 'Fe_diss_ugl',
      'Fe_ugl', 'Glyphosate_ugl', 'Hardnesscarbonate_mgl', 'K_mgl',
      'Linuron_ugl', 'MCPP_ugl', 'Mg_diss_mgl', 'Mg_mgl', 'Mn_diss_ugl',
      'Mn_ugl', 'NH3_N_diss_ugl', 'NH3_N_ugl', 'NO2_diss_ugl', 'NO3_diss_ugl',
      'NOx_ugl', 'Na_diss_mgl', 'Na_mgl', 'Ni_ugl', 'OP_mgl', 'Pb_ugl',
      'Pheo_ugl', 'SO4_diss_mgl', 'SO4_mgl', 'Salinity_PSS', 'Salinity_ppt',
      'Sb_ugl', 'Se_ugl', 'Secchi_ft', 'Si_ugl', 'Sucralose_ugl', 'TDS_mgl',
      'TKN_ugl', 'TN_ugl', 'TOC_mgl', 'TP_ugl', 'TSS_mgl', 'TempW_C',
      'TempW_F', 'Tl_ugl', 'Turb_ntu', 'Zn_ugl', 'pH'],
      dtype='object', name='Parameter')
```

```
[5]: Parameter  ActivityDepth  24D_ugl  Ag_ugl  Al_ugl  Alk_CaCO3_mgl  \
count          103.000000    5.000000   19.00    6.000000    34.000000
mean           0.385385    0.070100    0.01   28.833333   230.823529
std            0.146083    0.128781    0.00   13.556056    33.442597
min            0.100000    0.002000    0.01   11.000000   113.000000
25%            0.290000    0.008500    0.01   20.250000   205.750000
50%            0.500000    0.016000    0.01   30.000000   240.000000
75%            0.500000    0.024000    0.01   34.500000   250.000000
max            0.500000    0.300000    0.01   49.000000   289.000000
```

```
Parameter  As_ugl  BOD5_mgl  B_ugl  Ba_ugl  C_organic_mgl  ...  \
count      25.000000      1.0   6.000000   6.000000   19.000000  ...
mean       2.137200      1.0  72.700000  18.466667   15.842105  ...
std        0.500995   NaN  10.409611   1.155278    3.905312  ...
min        1.410000      1.0  57.900000  16.900000   10.000000  ...
25%        1.780000      1.0  66.900000  17.850000   12.500000  ...
50%        2.080000      1.0  73.100000  18.500000   15.000000  ...
75%        2.430000      1.0  78.025000  18.850000   17.500000  ...
max        3.480000      1.0  87.600000  20.300000   24.000000  ...
```

```
Parameter  TN_ugl  TOC_mgl  TP_ugl  TSS_mgl  TempW_C  \
count      72.000000   6.000000  94.000000  25.000000  95.000000
mean     1175.430556  16.666667  61.132979   5.840000  25.890333
std       427.584135   4.366539  50.033547   4.209909   4.203510
min       420.000000  11.000000   8.000000   2.000000  15.900000
25%       925.000000  13.250000  23.625000   3.000000  23.350000
50%      1092.500000  17.500000  48.500000   5.000000  26.900000
```

75%	1303.250000	19.500000	82.000000	7.000000	28.993333
max	2734.000000	22.000000	264.000000	22.000000	32.400000

Parameter	TempW_F	Tl_ugl	Turb_ntu	Zn_ugl	pH
count	95.000000	6.000000e+00	25.000000	21.000000	95.000000
mean	78.602600	1.000000e-01	6.344000	10.190476	7.557158
std	7.566317	1.520235e-17	3.446264	18.861652	0.336734
min	60.620000	1.000000e-01	2.900000	5.000000	6.790000
25%	74.030000	1.000000e-01	4.000000	5.000000	7.320000
50%	80.420000	1.000000e-01	5.200000	5.000000	7.500000
75%	84.188000	1.000000e-01	8.000000	5.000000	7.800000
max	90.320000	1.000000e-01	18.000000	89.000000	8.300000

[8 rows x 73 columns]

Not every parameter is measured on every date the survey of water is conducted.

```
[6]: input_data_pivot.isnull()
```

```
[6]: Parameter SampleDate ActivityDepth 24D_ugl Ag_ugl Al_ugl Alk_CaCO3_mgl \
0 False False True True True False
1 False False True True True True
2 False False True True True False
3 False False True True True True
4 False False True True True True
.. ...
98 False False True True True False
99 False False True True True True
100 False False True True True True
101 False False True True True True
102 False False True True True True
```

Parameter	As_ugl	BOD5_mgl	B_ugl	Ba_ugl	...	TN_ugl	TOC_mgl	TP_ugl	\
0	True	True	True	True	...	False	True	False	
1	True	True	True	True	...	False	True	False	
2	True	True	True	True	...	False	True	False	
3	True	True	True	True	...	False	True	False	
4	True	True	True	True	...	True	True	False	
..	...	...	...	...	...	...	...		
98	True	True	True	True	...	False	True	False	
99	True	True	True	True	...	False	True	False	
100	True	True	True	True	...	True	True	True	
101	False	True	True	True	...	False	False	False	
102	True	True	True	True	...	False	True	False	

Parameter	TSS_mgl	TempW_C	TempW_F	Tl_ugl	Turb_ntu	Zn_ugl	pH
0	True	False	False	True	True	True	False

1	True	False	False	True	True	True	False
2	True	False	False	True	True	True	False
3	True	False	False	True	True	True	False
4	True	False	False	True	True	True	False
..	...	...	...	...	...	...	...
98	True	False	False	True	True	True	False
99	True	False	False	True	True	True	False
100	True	False	False	True	True	True	False
101	False	False	False	True	False	True	False
102	True	False	False	True	True	True	False

[103 rows x 74 columns]

Percentage of missing values in each parameter

```
[7]: for i in range(len(input_data_pivot.columns)):
      missing_data = input_data_pivot[input_data_pivot.columns[i]].isna().sum()
      perc = missing_data / len(input_data_pivot) * 100
      print('>%d, missing entries: %d, percentage %.2f' % (i, missing_data,
      ↪perc))
```

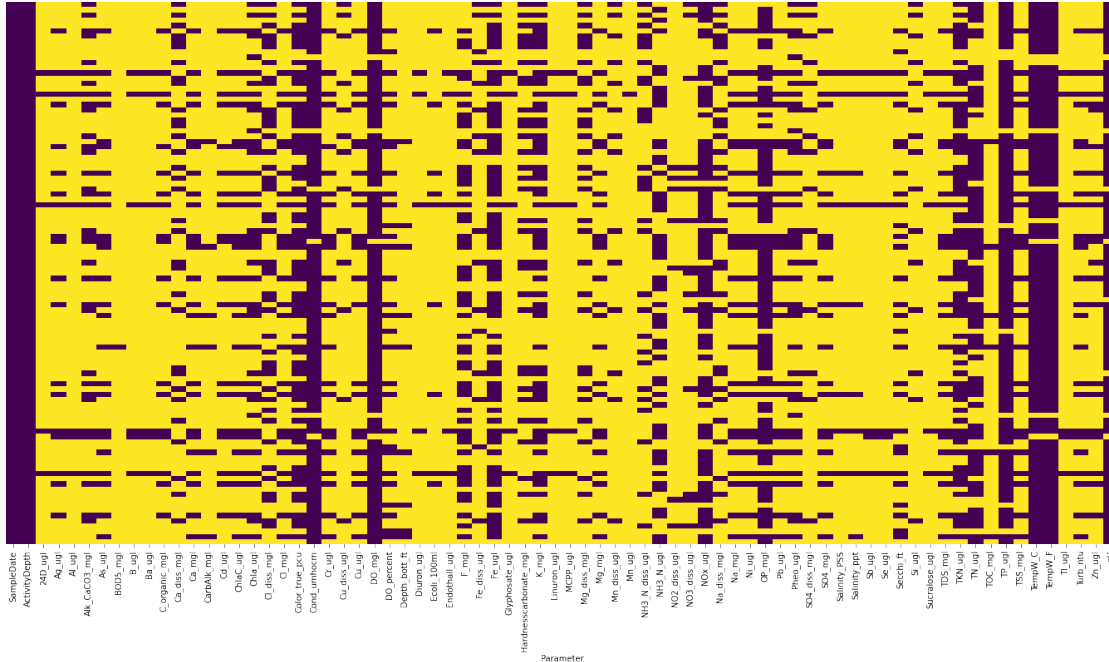
```
>0, missing entries: 0, percentage 0.00
>1, missing entries: 0, percentage 0.00
>2, missing entries: 98, percentage 95.15
>3, missing entries: 84, percentage 81.55
>4, missing entries: 97, percentage 94.17
>5, missing entries: 69, percentage 66.99
>6, missing entries: 78, percentage 75.73
>7, missing entries: 102, percentage 99.03
>8, missing entries: 97, percentage 94.17
>9, missing entries: 97, percentage 94.17
>10, missing entries: 84, percentage 81.55
>11, missing entries: 71, percentage 68.93
>12, missing entries: 78, percentage 75.73
>13, missing entries: 97, percentage 94.17
>14, missing entries: 84, percentage 81.55
>15, missing entries: 78, percentage 75.73
>16, missing entries: 63, percentage 61.17
>17, missing entries: 59, percentage 57.28
>18, missing entries: 78, percentage 75.73
>19, missing entries: 35, percentage 33.98
>20, missing entries: 6, percentage 5.83
>21, missing entries: 79, percentage 76.70
>22, missing entries: 90, percentage 87.38
>23, missing entries: 80, percentage 77.67
>24, missing entries: 6, percentage 5.83
>25, missing entries: 74, percentage 71.84
>26, missing entries: 94, percentage 91.26
```

>27, missing entries: 98, percentage 95.15  
>28, missing entries: 94, percentage 91.26  
>29, missing entries: 98, percentage 95.15  
>30, missing entries: 50, percentage 48.54  
>31, missing entries: 87, percentage 84.47  
>32, missing entries: 31, percentage 30.10  
>33, missing entries: 98, percentage 95.15  
>34, missing entries: 71, percentage 68.93  
>35, missing entries: 46, percentage 44.66  
>36, missing entries: 98, percentage 95.15  
>37, missing entries: 98, percentage 95.15  
>38, missing entries: 72, percentage 69.90  
>39, missing entries: 78, percentage 75.73  
>40, missing entries: 89, percentage 86.41  
>41, missing entries: 102, percentage 99.03  
>42, missing entries: 74, percentage 71.84  
>43, missing entries: 53, percentage 51.46  
>44, missing entries: 96, percentage 93.20  
>45, missing entries: 88, percentage 85.44  
>46, missing entries: 30, percentage 29.13  
>47, missing entries: 71, percentage 68.93  
>48, missing entries: 78, percentage 75.73  
>49, missing entries: 78, percentage 75.73  
>50, missing entries: 23, percentage 22.33  
>51, missing entries: 79, percentage 76.70  
>52, missing entries: 63, percentage 61.17  
>53, missing entries: 88, percentage 85.44  
>54, missing entries: 78, percentage 75.73  
>55, missing entries: 95, percentage 92.23  
>56, missing entries: 94, percentage 91.26  
>57, missing entries: 97, percentage 94.17  
>58, missing entries: 97, percentage 94.17  
>59, missing entries: 74, percentage 71.84  
>60, missing entries: 88, percentage 85.44  
>61, missing entries: 98, percentage 95.15  
>62, missing entries: 78, percentage 75.73  
>63, missing entries: 36, percentage 34.95  
>64, missing entries: 31, percentage 30.10  
>65, missing entries: 97, percentage 94.17  
>66, missing entries: 9, percentage 8.74  
>67, missing entries: 78, percentage 75.73  
>68, missing entries: 8, percentage 7.77  
>69, missing entries: 8, percentage 7.77  
>70, missing entries: 97, percentage 94.17  
>71, missing entries: 78, percentage 75.73  
>72, missing entries: 82, percentage 79.61  
>73, missing entries: 8, percentage 7.77

Heatmap of missing values in each parameter/column

```
[8]: plt.rcParams["figure.figsize"] = [24, 12]
sns.heatmap(input_data_pivot.isna(), cbar=False, cmap='viridis',
            yticklabels=False)
```

```
[8]: <AxesSubplot:xlabel='Parameter'>
```



From above figure, we can observe there are lot of missing data in every column except “SampleDate” and “ActivityDepth” which have no missing value.

Task 2 - Create plots for all the parameters with X-axis showing time and Y-axis showing the parameter value.

```
[9]: plt.style.use('classic')
      %matplotlib inline
      plt.rcParams["figure.figsize"] = [16, 12]
```

Saving plots in plots folder.

```
[10]: input_data_pivot.set_index('SampleDate', inplace=True)
      for i, col in enumerate(input_data_pivot.columns):
          input_data_pivot[col].plot(fig=plt.figure(i))
          plt.ion()
          plt.title(col)
          plt.xticks(rotation=90)
```



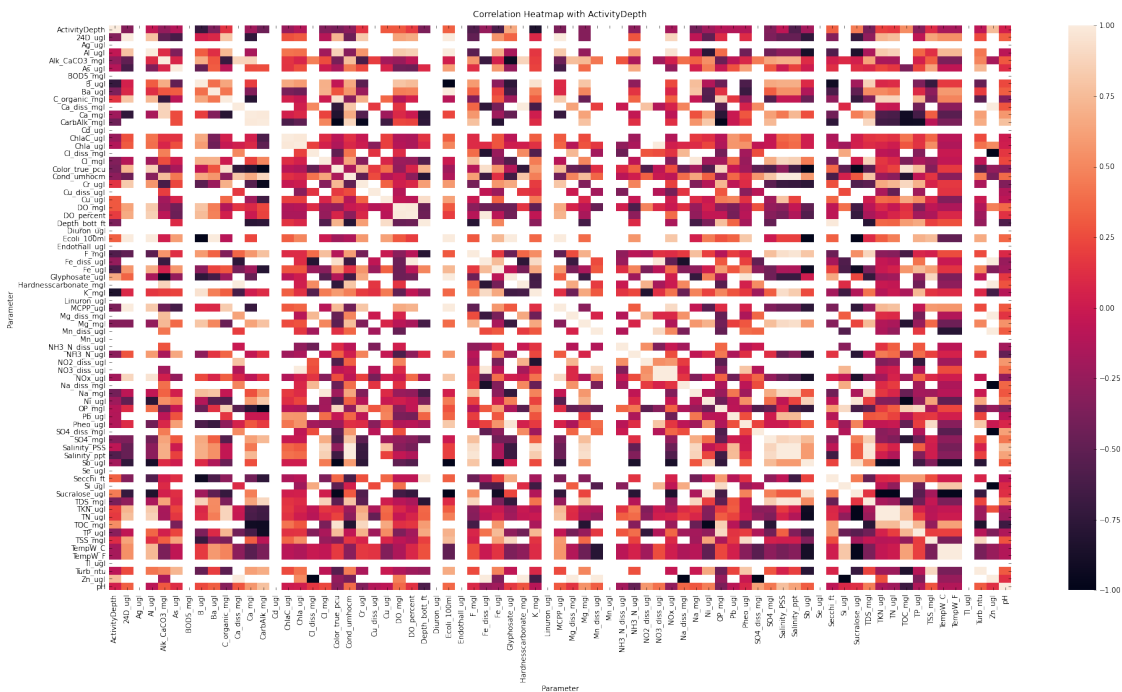
```
plt.tight_layout()
plt.savefig('./plots/'+str(col)+'.png', dpi=300)
plt.close()
```

Task 3 – List at least 3 feature pairs with strong correlations ( $> 0.5$  or  $< -0.5$ ) among them? Show heatmap of correlation, if possible. What does this indicate?

### Correlation Heatmap

```
[22]: corrl = input_data_pivot.corr()
# mask = np.triu(np.ones_like(input_data_pivot.corr(), dtype=bool))

# plotting the heatmap
plt.rcParams["figure.figsize"] = [28, 14]
heatmap = sns.heatmap(corrl)
heatmap.set_title('Correlation Heatmap with ActivityDepth',
fontdict={'fontsize':12}, pad=12);
```



Two Highest correlation: One is self and other is with different feature. We are concerned with other features not same feature for correlation.

```
[100]: corrl.reset_index()
for i, col in enumerate(corrl.columns):
    try:
```

```

        top = pd.DataFrame(corr1[(corr1[col]>0.9) | (corr1[col]<-0.9)][col].
↪nlargest(2).to_frame()).reset_index()
        top = top.drop(top[top["Parameter"]==col].index)
        if top.empty:
            pass
        else:
            print(top)
            print("\n")
    except:
        pass

```

```

        Parameter  24D_ugl
0  Ecoli_100ml      1.0

```

```

        Parameter  Al_ugl
0  Ecoli_100ml      1.0

```

```

        Parameter  Alk_CaCO3_mgl
1  Glyphosate_ugl      -0.925814

```

```

        Parameter    B_ugl
1    K_mgl  0.950117

```

```

        Parameter  Ba_ugl
0  Ecoli_100ml      1.0

```

```

        Parameter  C_organic_mgl
1  Color_true_pcu      0.939544

```

```

        Parameter  Ca_diss_mgl
1    Zn_ugl      1.0

```

```

        Parameter    Ca_mgl
1  CarbAlk_mgl  0.990536

```

```

        Parameter  CarbAlk_mgl
1    Ca_mgl      0.990536

```

Parameter ChlaC\_ugl  
1 Chla\_ugl 0.976938

Parameter Chla\_ugl  
1 NO3\_diss\_ugl 0.99939

Parameter Cl\_diss\_mgl  
1 Zn\_ugl -1.0

Parameter Cl\_mgl  
1 Na\_mgl 0.983395

Parameter Color\_true\_pcu  
1 TOC\_mgl 0.94758

Parameter Cond\_umhocm  
1 Salinity\_ppt 0.999392

Parameter Cr\_ugl  
1 CarbAlk\_mgl -0.958928

Parameter Cu\_ugl  
1 Depth\_bott\_ft 0.926694

Parameter DO\_mgl  
1 DO\_percent 0.988709

Parameter DO\_percent  
1 Fe\_diss\_ugl 0.998719

Parameter Depth\_bott\_ft  
1 Secchi\_ft 0.991882

Parameter Ecoli\_100ml  
0 24D\_ugl 1.0  
1 Al\_ugl 1.0

Parameter F\_mgl  
1 Salinity\_ppt 0.961899

Parameter Fe\_diss\_ugl  
1 Zn\_ugl 1.0

Parameter Fe\_ugl  
1 Sucralose\_ugl -0.915896

Parameter Glyphosate\_ugl  
1 Ecoli\_100ml 1.0

Parameter Hardnesscarbonate\_mgl  
1 Zn\_ugl 1.0

Parameter K\_mgl  
1 B\_ugl 0.950117

Parameter MCPP\_ugl  
1 Ecoli\_100ml 1.0

Parameter Mg\_diss\_mgl  
1 Zn\_ugl 1.0

Parameter Mg\_mgl  
1 Salinity\_ppt 0.936817

Parameter Mn\_diss\_ugl  
1 Zn\_ugl 1.0

Parameter N03\_diss\_ugl  
1 Chla\_ugl 0.99939

Parameter NOx\_ugl  
1 N03\_diss\_ugl 0.998936

Parameter Na\_diss\_mgl  
1 Zn\_ugl -1.0

Parameter Na\_mgl  
1 Cl\_mgl 0.983395

Parameter Ni\_ugl  
1 Sucralose\_ugl 0.961861

Parameter OP\_mgl  
1 Si\_ugl 0.910904

Parameter Pheo\_ugl  
1 Glyphosate\_ugl 0.962065

Parameter S04\_diss\_mgl  
1 Zn\_ugl -1.0

Parameter S04\_mgl  
1 Salinity\_ppt 0.913588

Parameter Salinity\_PSS  
1 Salinity\_ppt 1.0

Parameter Salinity\_ppt  
0 Salinity\_PSS 1.0

Parameter Sb\_ugl  
1 Sucralose\_ugl 0.936411

Parameter Secchi\_ft  
1 Depth\_bott\_ft 0.991882

Parameter Si\_ugl  
1 OP\_mgl 0.910904

	Parameter	Sucralose_ugl
1	Ni_ugl	0.961861

	Parameter	TDS_mgl
1	Salinity_PSS	0.977539

	Parameter	TKN_ugl
1	TN_ugl	0.993621

	Parameter	TN_ugl
1	TKN_ugl	0.993621

	Parameter	TOC_mgl
1	Color_true_pcu	0.94758

	Parameter	TP_ugl
1	OP_mgl	0.902318

	Parameter	TSS_mgl
1	Pheo_ugl	0.915603

	Parameter	TempW_C
1	TempW_F	1.0

	Parameter	TempW_F
1	TempW_C	1.0

	Parameter	Zn_ugl
0	Fe_diss_ugl	1.0
1	Hardnesscarbonate_mgl	1.0

Top three correlated feature pairs are when considering ActivityDepth:

1. Ecoli\_100ml and Al\_ugl
2. Zn\_ugl and Si\_ugl
3. DO\_percent and Fe\_diss\_ugl

```
[102]: # Imputing missing values
# imputer = SimpleImputer(missing_values=np.NaN, strategy='median')
# for i in range(len(input_data_pivot_drop_activitydepth.columns)):
#     input_data_pivot_drop_activitydepth[input_data_pivot_drop_activitydepth.
#     ↪columns[i]] = imputer.
#     ↪fit_transform(input_data_pivot_drop_activitydepth[input_data_pivot_drop_activitydepth.
#     ↪columns[i]].values.reshape(-1,1))[:,0]

# input_data_pivot_drop_activitydepth
```

**Task 4 – If you are a resident living near this location and looking at this water data. You want to know answers for questions like if it safe to go to swim in the water, use water to irrigate your garden or event drink from it? Can this data answer any such questions? Discuss. .**

If I am residing near this location, I would be interested to know:

1. The pH value of the water, tells the acidic level of water.
2. The amount of dissolved calcium and magnesium in the water, it defines the hardness of water.
3. The temperature of the water. It affects fish and aquatic plants in the water.
5. Salinity of water
6. Turbidity of water
7. Alkalinity of water
8. Dissolved oxygen content in water
9. Phosphorus and Nitrogen content of water.

Basically, by looking at this I want to know the quality of the water before using it to drink, cook food, swimming, fishing, etc. As the contains the parameters I will mostly be interested in to know, I think I will able to judge the quality of water in this location.

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