In [1]:

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

In [2]:

```
df=pd.read_csv("9_bottle.csv")
df
```

```
C:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3165: DtypeW
arning: Columns (47,73) have mixed types.Specify dtype option on import or set low_memor
y=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[2]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.500	33.4400	NaN	25.64900	NaN	...	
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.460	33.4400	NaN	25.65600	NaN	...	
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.460	33.4370	NaN	25.65400	NaN	...	
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.450	33.4200	NaN	25.64300	NaN	...	
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.450	33.4210	NaN	25.64300	NaN	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-	0	18.744	33.4083	5.805	23.87055	108.74	...	

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R
				09340264-0000A-7								
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	18.744	33.4083	5.805	23.87072	108.74	...	
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	18.692	33.4150	5.796	23.88911	108.46	...	
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	18.161	33.4062	5.816	24.01426	107.74	...	
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	17.533	33.3880	5.774	24.15297	105.66	...	

864863 rows × 74 columns

In [3]:

```
df.head()
```

Out[3]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.50	33.440	NaN	25.649	NaN	...	NaN
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.46	33.440	NaN	25.656	NaN	...	NaN
2	1	3	054.0 056.0	19-4903CR-HY-060-	10	10.46	33.437	NaN	25.654	NaN	...	NaN

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO
				0930-05400560-0010A-7								
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.45	33.420	NaN	25.643	NaN	...	NaN
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.45	33.421	NaN	25.643	NaN	...	NaN

5 rows × 74 columns

DATA CLEANING AND DATA PREPROCESSING

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 864863 entries, 0 to 864862
Data columns (total 74 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   Cst_Cnt              864863 non-null  int64  
 1   Btl_Cnt              864863 non-null  int64  
 2   Sta_ID               864863 non-null  object 
 3   Depth_ID             864863 non-null  object 
 4   Depthm               864863 non-null  int64  
 5   T_degC               853900 non-null  float64
 6   Salnty               817509 non-null  float64
 7   O2ml_L               696201 non-null  float64
 8   STheta               812174 non-null  float64
 9   O2Sat                661274 non-null  float64
 10  Oxy_µmol/Kg          661268 non-null  float64
 11  BtlNum               118667 non-null  float64
 12  RecInd               864863 non-null  int64  
 13  T_prec               853900 non-null  float64
 14  T_qual               23127 non-null   float64
 15  S_prec               817509 non-null  float64
 16  S_qual               74914 non-null   float64
 17  P_qual               673755 non-null  float64
 18  O_qual               184676 non-null  float64
 19  SThtaq               65823 non-null   float64
 20  O2Satq               217797 non-null  float64
 21  ChlorA               225272 non-null  float64
 22  Chlqua               639166 non-null  float64
 23  Phaeop               225271 non-null  float64
 24  Phaqua               639170 non-null  float64
 25  PO4uM                413317 non-null  float64
```

```
 26  PO4q               451786 non-null  float64
 27  SiO3uM             354091 non-null  float64
 28  SiO3qu             510866 non-null  float64
 29  NO2uM              337576 non-null  float64
 30  NO2q               529474 non-null  float64
 31  NO3uM              337403 non-null  float64
 32  NO3q               529933 non-null  float64
 33  NH3uM              64962 non-null   float64
 34  NH3q               808299 non-null  float64
 35  C14As1             14432 non-null   float64
 36  C14A1p             12760 non-null   float64
 37  C14A1q             848605 non-null  float64
 38  C14As2             14414 non-null   float64
 39  C14A2p             12742 non-null   float64
 40  C14A2q             848623 non-null  float64
 41  DarkAs             22649 non-null   float64
 42  DarkAp             20457 non-null   float64
 43  DarkAq             840440 non-null  float64
 44  MeanAs             22650 non-null   float64
 45  MeanAp             20457 non-null   float64
 46  MeanAq             840439 non-null  float64
 47  IncTim             14437 non-null   object
 48  LightP             18651 non-null   float64
 49  R_Depth            864863 non-null  float64
 50  R_TEMP             853900 non-null  float64
 51  R_POTEMP           818816 non-null  float64
 52  R_SALINITY         817509 non-null  float64
 53  R_SIGMA            812007 non-null  float64
 54  R_SVA              812092 non-null  float64
 55  R_DYNHT            818206 non-null  float64
 56  R_O2               696201 non-null  float64
 57  R_O2Sat            666448 non-null  float64
 58  R_SIO3             354099 non-null  float64
 59  R_PO4              413325 non-null  float64
 60  R_NO3              337411 non-null  float64
 61  R_NO2              337584 non-null  float64
 62  R_NH4              64982 non-null   float64
 63  R_CHLA             225276 non-null  float64
 64  R_PHAEO            225275 non-null  float64
 65  R_PRES             864863 non-null  int64
 66  R_SAMP             122006 non-null  float64
 67  DIC1               1999 non-null    float64
 68  DIC2               224 non-null     float64
 69  TA1                2084 non-null    float64
 70  TA2                234 non-null     float64
 71  pH2                10 non-null      float64
 72  pH1                84 non-null      float64
 73  DIC Quality Comment  55 non-null    object
dtypes: float64(65), int64(5), object(4)
memory usage: 488.3+ MB
```

In [5]:

```
df.describe()
```

Out[5]:

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_L	
count	864863.000000	864863.000000	864863.000000	853900.000000	817509.000000	696201.000000	81217
mean	17138.790958	432432.000000	226.831951	10.799677	33.840350	3.392468	2
std	10240.949817	249664.587267	316.050259	4.243825	0.461843	2.073256	
min	1.000000	1.000000	0.000000	1.440000	28.431000	-0.010000	2
25%	8269.000000	216216.500000	46.000000	7.680000	33.488000	1.360000	2

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_L	
50%	16848.000000	432432.000000	125.000000	10.060000	33.863000	3.440000	2
75%	26557.000000	648647.500000	300.000000	13.880000	34.196900	5.500000	2
max	34404.000000	864863.000000	5351.000000	31.140000	37.034000	11.130000	25

8 rows × 70 columns

In [6]:

```
df.columns
```

Out[6]:

```
Index(['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'T_degC',
       'Salnty', 'O2ml_L', 'STheta', 'O2Sat', 'Oxy_µmol/Kg', 'BtlNum',
       'RecInd', 'T_prec', 'T_qual', 'S_prec', 'S_qual', 'P_qual', 'O_qual',
       'SThtaq', 'O2Satq', 'ChlorA', 'Chlqua', 'Phaeop', 'Phaqua', 'PO4uM',
       'PO4q', 'SiO3uM', 'SiO3qu', 'NO2uM', 'NO2q', 'NO3uM', 'NO3q', 'NH3uM',
       'NH3q', 'C14As1', 'C14A1p', 'C14A1q', 'C14As2', 'C14A2p', 'C14A2q',
       'DarkAs', 'DarkAp', 'DarkAq', 'MeanAs', 'MeanAp', 'MeanAq', 'IncTim',
       'LightP', 'R_Depth', 'R_TEMP', 'R_POTEMP', 'R_SALINITY', 'R_SIGMA',
       'R_SVA', 'R_DYNHT', 'R_O2', 'R_O2Sat', 'R_SIO3', 'R_PO4', 'R_NO3',
       'R_NO2', 'R_NH4', 'R_CHLA', 'R_PHAEO', 'R_PRES', 'R_SAMP', 'DIC1',
       'DIC2', 'TA1', 'TA2', 'pH2', 'pH1', 'DIC Quality Comment'],
      dtype='object')
```

In [7]:

```
df1=df.dropna(axis=1)
df1
```

Out[7]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	RecInd	R_Depth	R_PRES
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	3	0.0	0
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	3	8.0	8
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	7	10.0	10
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	3	19.0	19
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	7	20.0	20
...	...	...	...	...	...	...	...	...
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-09340264-0000A-7	0	7	0.0	0
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	3	2.0	2
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	3	5.0	5
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	3	10.0	10

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	RecInd	R_Depth	R_PRES
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	3	15.0	15

864863 rows × 8 columns

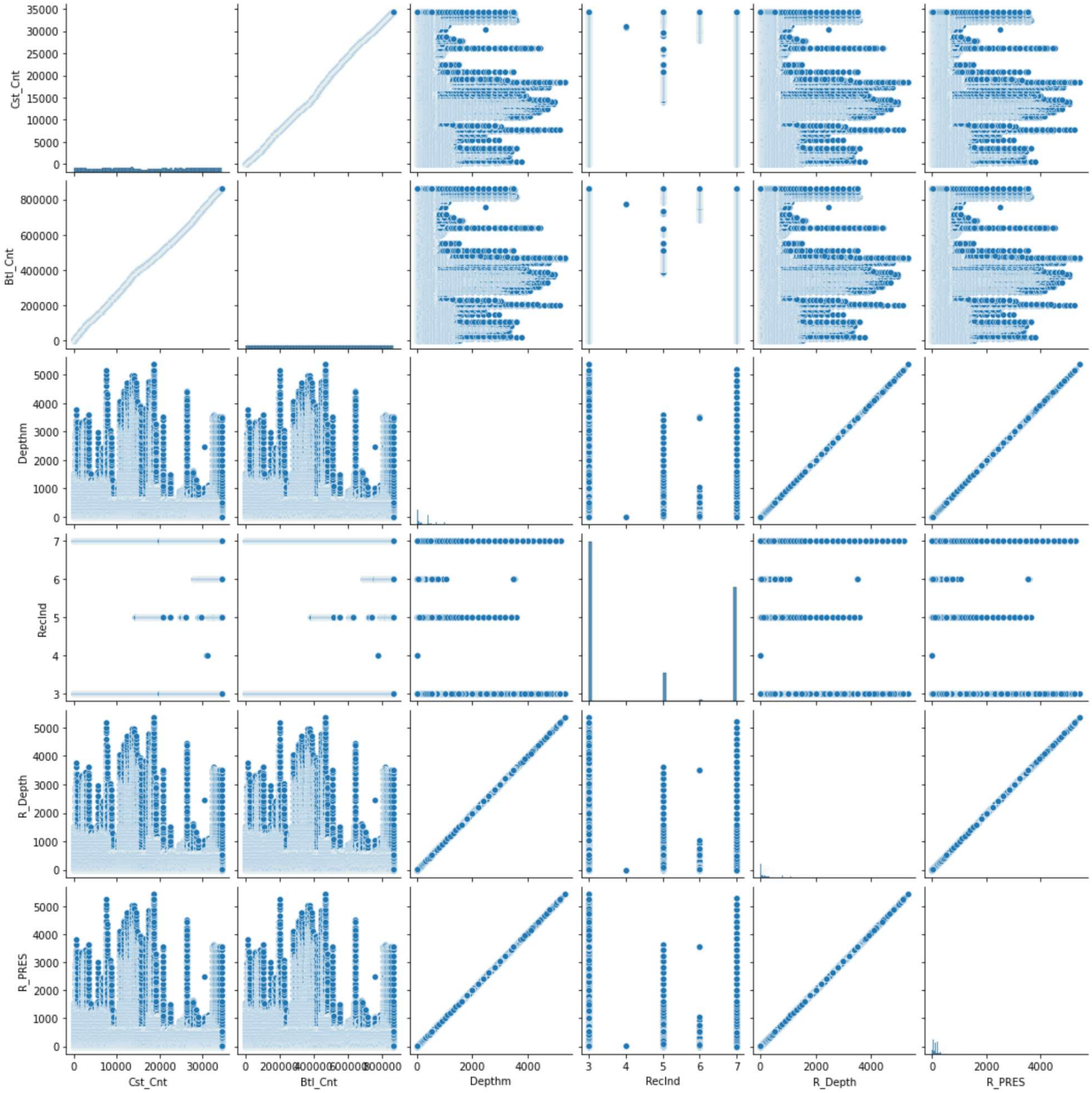
In [8]:
```
df1.columns
```

Out[8]:
```
Index(['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'RecInd',
       'R_Depth', 'R_PRES'],
      dtype='object')
```

EDA AND VISUALIZATION

In [9]:
```
sns.pairplot(df1)
```

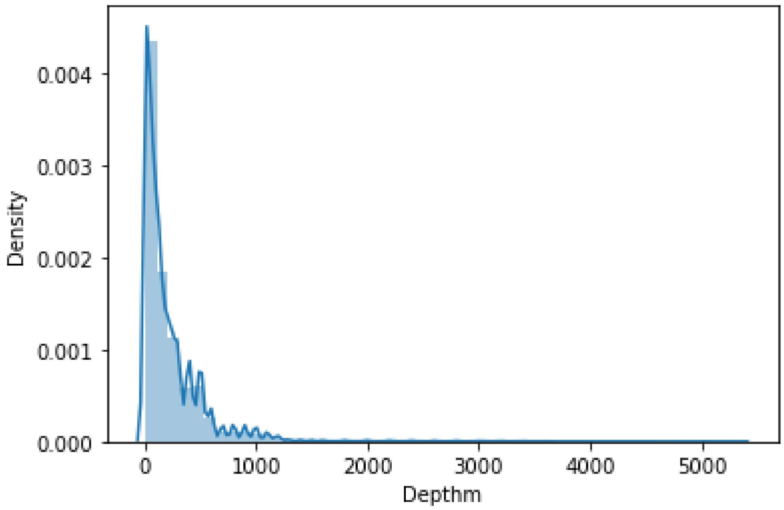
Out[9]:
```
<seaborn.axisgrid.PairGrid at 0x2e08005f070>
```



In [10]:
```
sns.distplot(df1['Depthm'])
```

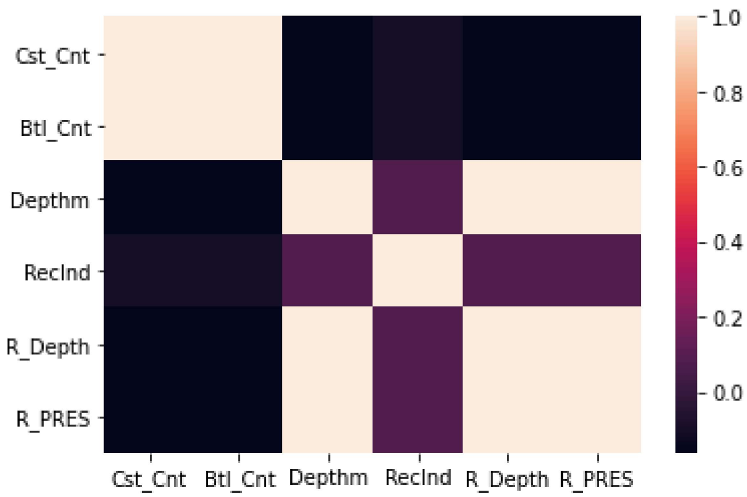
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
t your code to use either `displot` (a figure-level function with similar flexibility) o
r `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[10]: <AxesSubplot:xlabel='Depthm', ylabel='Density'>



In [11]:
```
sns.heatmap(df1.corr())
```

Out[11]: <AxesSubplot:>



TO TRAIN THE MODEL AND MODEL BULDING

In [12]:
```
x=df[['Cst_Cnt', 'Btl_Cnt', 'Depthm', 'RecInd','R_Depth']]
y=df['R_PRES']
```

In [13]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [14]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]: LinearRegression()

In [15]:
```
lr.intercept_
```

Out[15]: -1.050918565810889

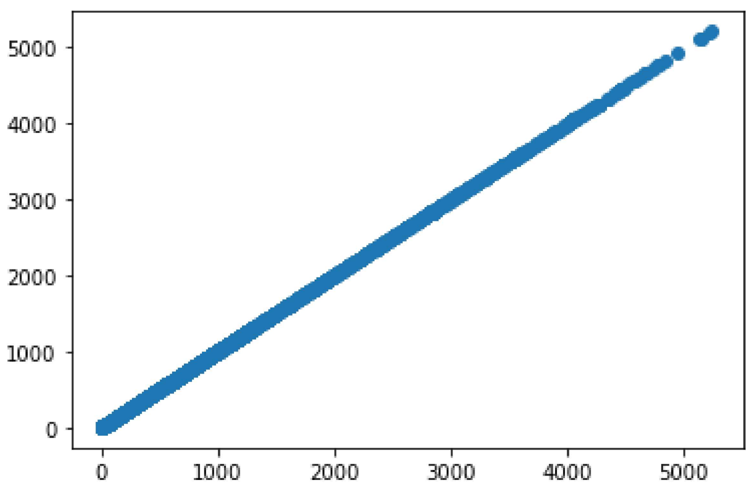
In [16]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
Cst_Cnt	-0.000162
Btl_Cnt	0.000007
Depthm	-0.687010
RecInd	-0.018467
R_Depth	1.697846

In [17]:
```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[17]: <matplotlib.collections.PathCollection at 0x2e0a6ee1e80>



ACCURACY

In [18]:
```
lr.score(x_test,y_test)
```

Out[18]: 0.9999882064228681

In [19]:
```
lr.score(x_train,y_train)
```

Out[19]: 0.9999878895315537

In [20]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [21]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```
Out[21]: Ridge(alpha=10)

In [22]:
```
rr.score(x_test,y_test)
```
Out[22]: 0.9999882064008344

In [23]:
```
rr.score(x_train,y_train)
```
Out[23]: 0.999987889506774

In [24]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```
Out[24]: Lasso(alpha=10)

In [25]:
```
la.score(x_train,y_train)
```
Out[25]: 0.999987819508951

In [26]:
```
la.score(x_test,y_test)
```
Out[26]: 0.9999881392636941

In [27]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```
Out[27]: ElasticNet()

In [28]:
```
en.coef_
```
Out[28]:
```
array([-7.93126465e-06,  6.78609126e-07,  1.01080491e+00, -0.00000000e+00,
        2.05266837e-05])
```

In [29]:
```
en.intercept_
```
Out[29]: -1.0499131421797756

In [30]:
```
prediction=en.predict(x_test)
```

In [31]:
```
en.score(x_test,y_test)
```

Out[31]: 0.9999881402856057

In [32]:

```
from sklearn import metrics
print(metrics.mean_absolute_error(y_test,prediction))
print(metrics.mean_squared_error(y_test,prediction))
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
0.6477107548609093
1.1999281682906833
1.095412327980055
```