# A report on the relationship between salinity, temperature and depth in the ocean.

## 1 Introduction

The California Cooperative Oceanic Fisheries Investigations (CalCOFI) is a unique partnership of the California Department of Fish & Wildlife, NOAA Fisheries Service and Scripps Institution of Oceanography. In this project we are using the dataset prepared by this organization which includes a lot of physical, chemical and biological data collected in different time intervals and different space in an ocean. Data of temperature, salinity, oxygen, phosphate, silicate, nitrate and nitrite, chlorophyll, transmissometer, PAR, C14 primary productivity, phytoplankton biodiversity, zooplankton biomass, and zooplankton biodiversity are collected and stored in csv file.

I used this dataset from Kaggle : https://www.kaggle.com/datasets/sohier/calcofi Since we have many different oceanographic data, in this project we are particularly interested in two features in an ocean viz. Temperature and Salinity. We are also interested in the relation between temperature and depth. Salinity is a measure of salt concentration in water. There are 864850 unique instances in the dataset. Since this is a fairly big enough dataset, we will try to answer some research questions.

## 2 Objectives

To answer the following research questions: 1. Is it possible to predict salinity depending upon the water temperature in oceans ? 2. What kind of relationship exists between temperature and salinity (if any) ? 3. How does temperature change with depth in the ocean ? 4. Can we predict temperature in the ocean given the depth ?

## 3 Methodology

I am approaching this problem by using data analysis techniques and applying regression models in python. Since we have to establish relation between two variables only in each research objective, regression techniques can help discover any relation between variables.

## 4 Data Analysis

Let's proceed by loading the dataset.

### 4.1 Data Loading

Importing important python libraries and loading the dataset with pandas read_csv(). Original dimensions of the dataset : 864863 rows × 74 columns. Let's start inspecting some aspects of the dataset.

[68]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import Normalizer, StandardScaler
from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error
```

[3]:
```
data = pd.read_csv("bottle.csv")
```

```
C:\Users\Bishal\AppData\Local\Temp\ipykernel_5068\1660720635.py:1: DtypeWarning:
Columns (47,73) have mixed types. Specify dtype option on import or set
low_memory=False.
  data = pd.read_csv("bottle.csv")
```

### 4.2 Data Inspection and Manipulation

[4]:
```
data.head()
```

[4]:
```
   Cst_Cnt  Btl_Cnt       Sta_ID                                Depth_ID  \
0        1        1  054.0 056.0  19-4903CR-HY-060-0930-05400560-0000A-3
1        1        2  054.0 056.0  19-4903CR-HY-060-0930-05400560-0008A-3
2        1        3  054.0 056.0  19-4903CR-HY-060-0930-05400560-0010A-7
3        1        4  054.0 056.0  19-4903CR-HY-060-0930-05400560-0019A-3
4        1        5  054.0 056.0  19-4903CR-HY-060-0930-05400560-0020A-7

   Depthm  T_degC  Salnty  O2ml_L  STheta  O2Sat  ...  R_PHAEO  R_PRES  \
0       0   10.50  33.440     NaN  25.649    NaN  ...      NaN       0
1       8   10.46  33.440     NaN  25.656    NaN  ...      NaN       8
2      10   10.46  33.437     NaN  25.654    NaN  ...      NaN      10
3      19   10.45  33.420     NaN  25.643    NaN  ...      NaN      19
4      20   10.45  33.421     NaN  25.643    NaN  ...      NaN      20

   R_SAMP  DIC1  DIC2  TA1  TA2  pH2  pH1  DIC Quality Comment
0     NaN   NaN   NaN  NaN  NaN  NaN  NaN                  NaN
1     NaN   NaN   NaN  NaN  NaN  NaN  NaN                  NaN
2     NaN   NaN   NaN  NaN  NaN  NaN  NaN                  NaN
3     NaN   NaN   NaN  NaN  NaN  NaN  NaN                  NaN
4     NaN   NaN   NaN  NaN  NaN  NaN  NaN                  NaN
```

```
[5 rows x 74 columns]
```

[205]:
```
data.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
```

There are 74 columns, i.e. 74 variables. Since we are working with only three features here, data segregation was done. 'Depthm' stores depth in the ocean in meters, 'T_degC' represents temperature in degrees celsius and 'Salnty' represents salinity in g of salt per kg of water (g/kg).

[5]:
```
data = data[['Depthm', 'T_degC', 'Salnty']]
```

[6]:
```
data
```

```
[6]:          Depthm  T_degC   Salnty
      0            0  10.500  33.4400
      1            8  10.460  33.4400
      2           10  10.460  33.4370
      3           19  10.450  33.4200
      4           20  10.450  33.4210
      ...        ...     ...      ...
      864858       0  18.744  33.4083
      864859       2  18.744  33.4083
      864860       5  18.692  33.4150
      864861      10  18.161  33.4062
      864862      15  17.533  33.3880

      [864863 rows x 3 columns]
```

This is the data that we will proceed further with. Data was not clean i.e. there were some missing values. To see all the rows containing missing values, we run the following command and proceed further.

### 4.3 Data Cleaning

```
[7]: data[data.isna().any(axis = 1)]
```

```
[7]:          Depthm  T_degC  Salnty
      17         221    8.45     NaN
      98          40    9.97     NaN
      129         37   10.20     NaN
      222         37   12.23     NaN
      264        246     NaN   33.95
      ...        ...     ...     ...
      810515      10   14.88     NaN
      810524      10   15.10     NaN
      811305      10   15.27     NaN
      828253       0   13.58     NaN
      828290       0   13.34     NaN

      [50616 rows x 3 columns]
```

Seeing the percentage of data containing null values.

```
[8]: missing_percentage = data.isnull().sum()*100 / len(data)
     missing_df = pd.DataFrame({'Columns': data.columns, 'Missing Percentage':␣
      ↪missing_percentage})
     missing_df
```

```
[8]:         Columns  Missing Percentage
      Depthm  Depthm            0.000000
      T_degC  T_degC            1.267600
```

```
Salnty   Salnty           5.475318
```

I was interested in the percentage of null values in each row because the dataset was big and the only metric to identify the volume of null values would be the percentage of null values for each variable. Since the percentage of null values was 1.26% in the 'T_degC' column and 5.47% in the 'Salnty' column and 0% in the 'Depthm' column, I handled these missing values by replacing them with the median value in each column.

[9]:
```
data = data.fillna(data.median())
```

[10]:
```
missing_percentage = data.isnull().sum()*100 / len(data)
missing_df = pd.DataFrame({ 'Missing Percentage': missing_percentage})
missing_df
```

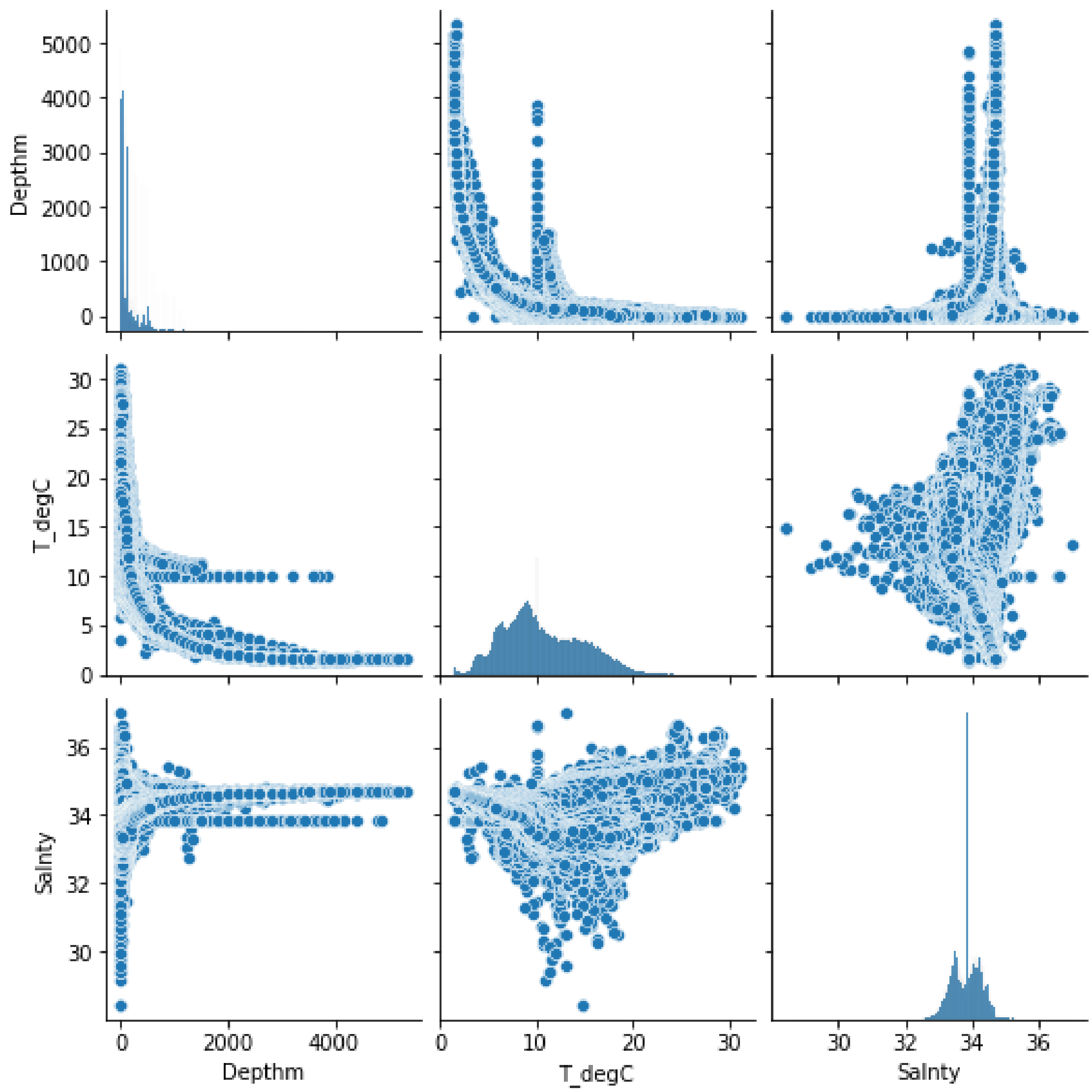
[10]:

| | Missing Percentage |
|---|---|
| Depthm | 0.0 |
| T_degC | 0.0 |
| Salnty | 0.0 |

Snippet above confirms that we replaced all the missing values. Now, it's time to start looking into the relation between variables. Let's first look at the correlation between variables. Scatterplot is a good way of visualizing relations between variables.

[12]:
```
sns.pairplot(data)
```

[12]: <seaborn.axisgrid.PairGrid at 0x24943469720>




Well, inspecting the above scatterplot, we can get some insights on how each variable behaves on increasing or decreasing the value of each other variable. Let's look at the scatterplot of 'Depthm' and 'T_degC', we see that they are related but not linearly. We can say that there exists a polynomial relationship between depth and temperature in the ocean. It gives us a reason to use nonlinear regression models in our analysis later on. Similarly, temperature versus salinity looks very random, we will explore the underlying relationship later .

For now, let's try to mathematically understand the graph we just saw .

[11]:
```
data.corr()
```

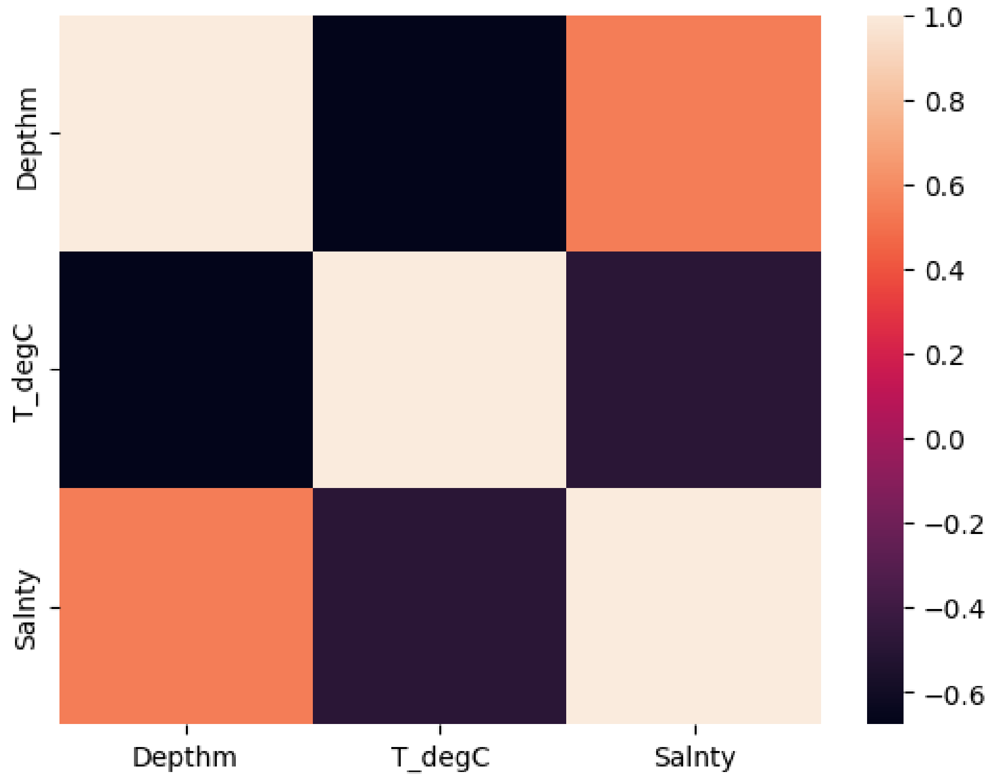
[11]:

| | Depthm | T_degC | Salnty |
|---|---|---|---|
| Depthm | 1.000000 | -0.677582 | 0.544113 |
| T_degC | -0.677582 | 1.000000 | -0.490233 |

```
Salnty  0.544113 -0.490233  1.000000
```

[13]:
```
sns.heatmap(data.corr())
```

[13]:
```
<AxesSubplot:>
```




Looking at the heatmap and correlation values, we find that temperature and depth show fairly strong negative correlation (-0.67). Similarly depth and salinity have correlation coefficient of 0.54 which shows fairly strong positive correlation. Similarly correlation coefficient of -0.49 shows mild negative correlation between temperature and salinity.

[21]:
```
std = StandardScaler()
scaled = std.fit_transform(data)
scaled_df = pd.DataFrame(scaled, columns = data.columns)
```

Now we need to scale the dataset to turn it into a standard distribution so that we can get a better regression line while fitting the regression model. Following code snippet does that.

[22]:
```
scaled_df
```

[22]:
```
          Depthm    T_degC    Salnty
0      -0.717709 -0.068830 -0.894309
1      -0.692396 -0.078314 -0.894309
```

```
2       -0.686068 -0.078314 -0.900990
3       -0.657592 -0.080685 -0.938848
4       -0.654428 -0.080685 -0.936621
...           ...       ...       ...
864858 -0.717709  1.885813 -0.964903
864859 -0.711381  1.885813 -0.964903
864860 -0.701889  1.873483 -0.949982
864861 -0.686068  1.747584 -0.969579
864862 -0.670248  1.598686 -1.010109

[864863 rows x 3 columns]
```

Let's look at the heatmap and correlation matrix again, is there any improvement?

[23]:
```
data.corr()
```

[23]:

| | Depthm | T_degC | Salnty |
|---|---|---|---|
| Depthm | 1.000000 | -0.677582 | 0.544113 |
| T_degC | -0.677582 | 1.000000 | -0.490233 |
| Salnty | 0.544113 | -0.490233 | 1.000000 |

We won't see improvement because StandardScaler only scales the same dataset into comparable scales. Now we will separate the target variable and input variable. We want Temperature to be input variable for us to predict the target variable i.e. Salinity. Reshaping is needed so that we can easily fit regression models.

[25]:
```
X = scaled_df['T_degC'].to_numpy().reshape(-1,1)
Y = scaled_df['Salnty'].to_numpy().reshape(-1,1)
```

Now we can use the scaled dataset to create a training and testing set.

[26]:
```
X_train,X_test,Y_train,Y_test = train_test_split(X, Y, test_size = 0.3)
```

Therefore, we can fit the LinearRegression model and analyze the results.

# 5 Results and Findings

### 5.0.1 Temperature and Salinity

Implementing linear regression:

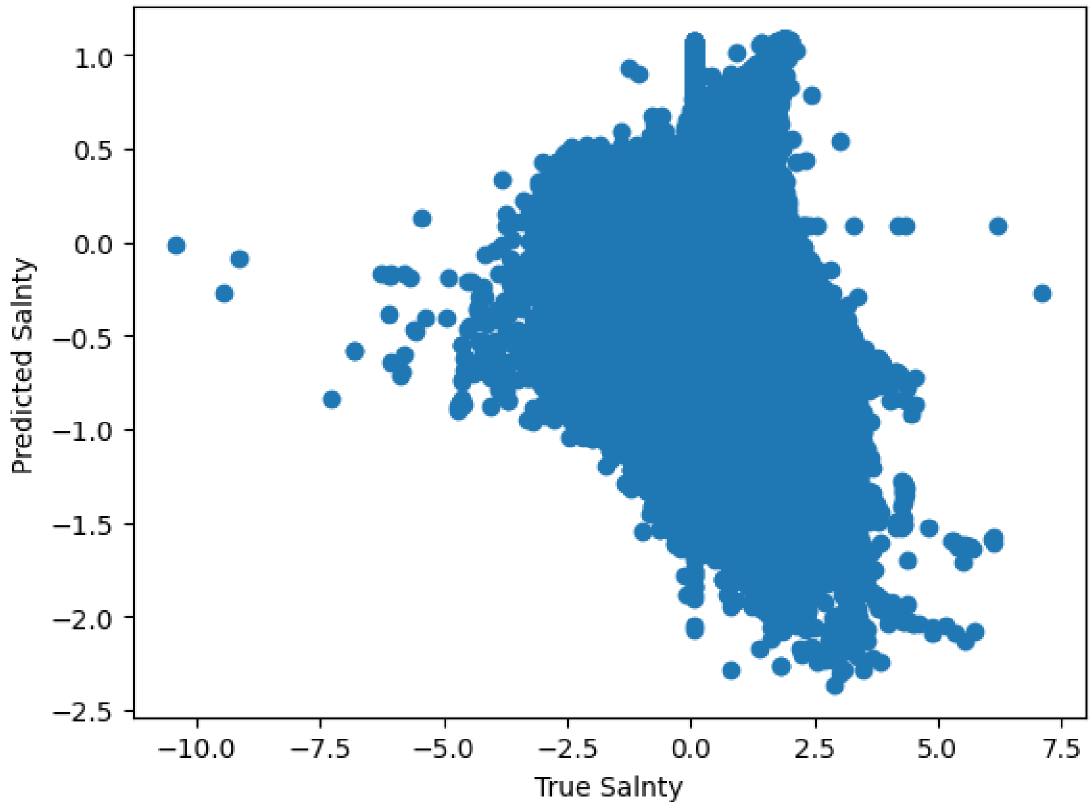
[27]:
```
model = LinearRegression()

model.fit(X_train,Y_train)
print(f'Score:{model.score(X_test, Y_test)} \nCoefficient:{model.coef_[0]}␣
 ↪\nIntercept:{model.intercept_}')
Y_pred = model.predict(X_test)
plt.scatter(Y_test,Y_pred)
plt.xlabel('True Salnty')
```

```
plt.ylabel('Predicted Salnty')

m = model.coef_[0]
c = model.intercept_
```

```
Score:0.2395988416799122
Coefficient:[-0.49061534]
Intercept:[1.57738579e-05]
```

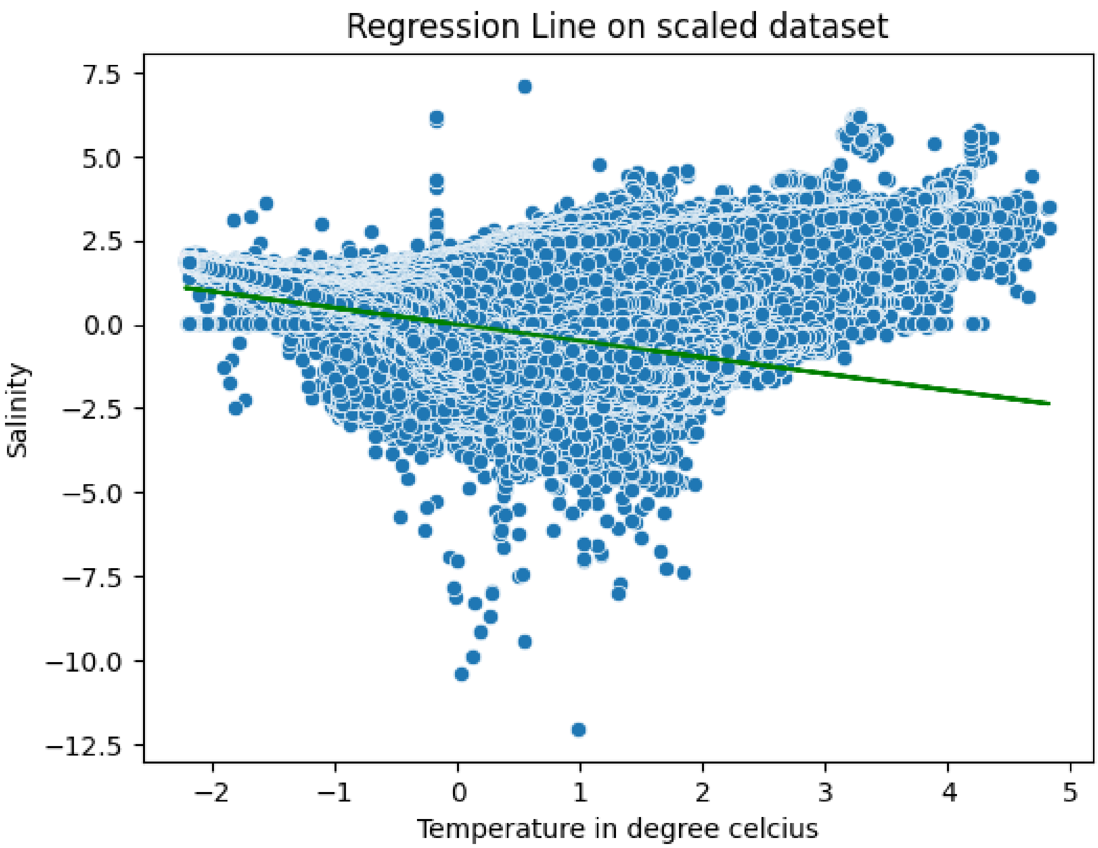



Above implementation of linear regression seeks to predict salinity based on the temperature values. The model has an R squared score of 0.2398. The graph between true value of salinity and predicted value of salinity can be observed and it shows the result is poor. This model is a poor fit. Since we have got the coefficient and intercept value for the regression line, we can plot it.

[221]:
```
x = scaled_df['T_degC']
y = m*x + c
```

[222]:
```
sns.scatterplot(x = 'T_degC', y = 'Salnty', data = scaled_df)
plt.plot(x, y, color = 'green')
plt.title('Regression Line on scaled dataset')
plt.ylabel('Salinity')
plt.xlabel('Temperature in degree celcius')
```

[222]: Text(0.5, 0, 'Temperature in degree celcius')




Also, we want to look at the other metric that is root mean squared error.

[223]:
```
r2 = r2_score(Y_test, Y_pred)
rmse = mean_squared_error(Y_test, Y_pred, squared = True)
print(f'R2 Score: {r2} \nRMSE : {rmse}')
```

```
R2 Score: 0.23989473410464568
RMSE : 0.7606037393911257
```

Above data is for the scaled dataset. We got a better rmse value for the dataset which was not scaled as shown below:

[227]:
```
X = data['T_degC'].to_numpy().reshape(-1,1)
Y = data['Salnty'].to_numpy().reshape(-1,1)
```

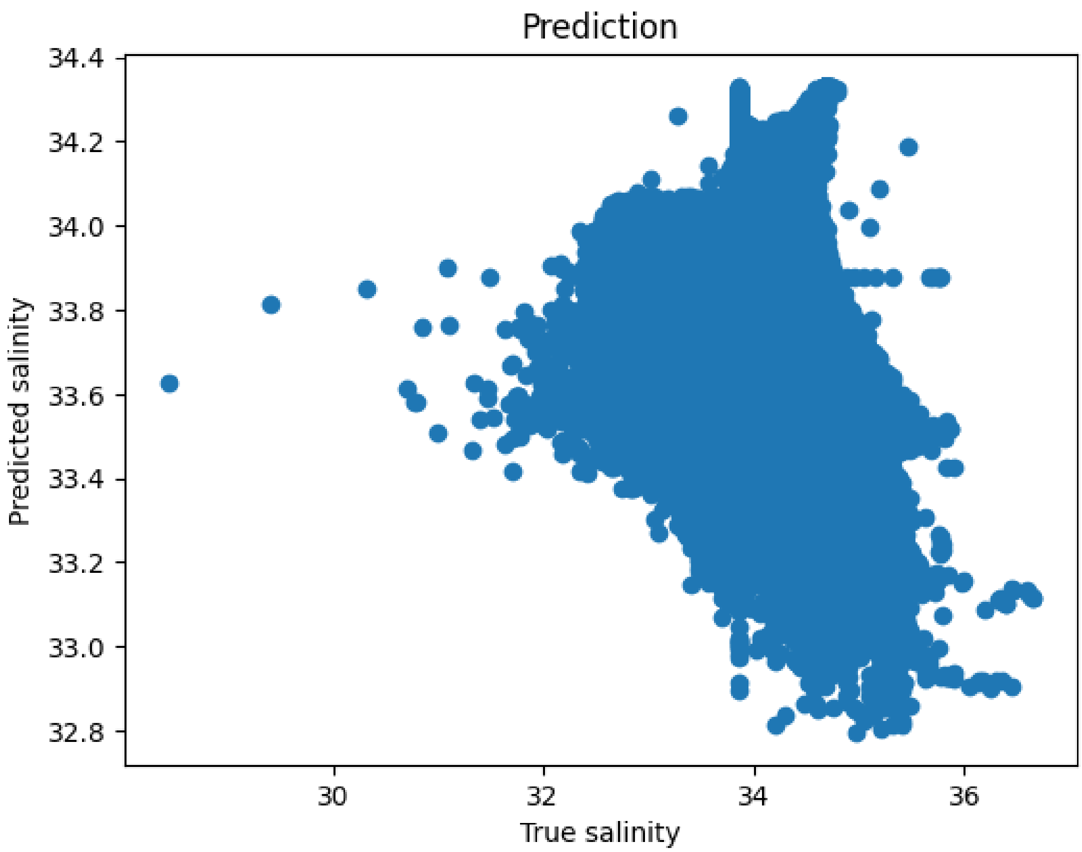
[228]:
```
X_train,X_test,Y_train,Y_test = train_test_split(X, Y, test_size = 0.3)
model = LinearRegression()

model.fit(X_train,Y_train)
```

```
print(f'Score:{model.score(X_test, Y_test)} \nCoefficient:{model.coef_[0]}␣
 ↪\nIntercept:{model.intercept_}')
Y_pred = model.predict(X_test)
plt.scatter(Y_test,Y_pred)
plt.xlabel('True salinity')
plt.ylabel('Predicted salinity')
plt.title('Prediction')

m = model.coef_[0]
c = model.intercept_
```

```
Score:0.23655720111415657
Coefficient:[-0.05236094]
Intercept:[34.4065459]
```



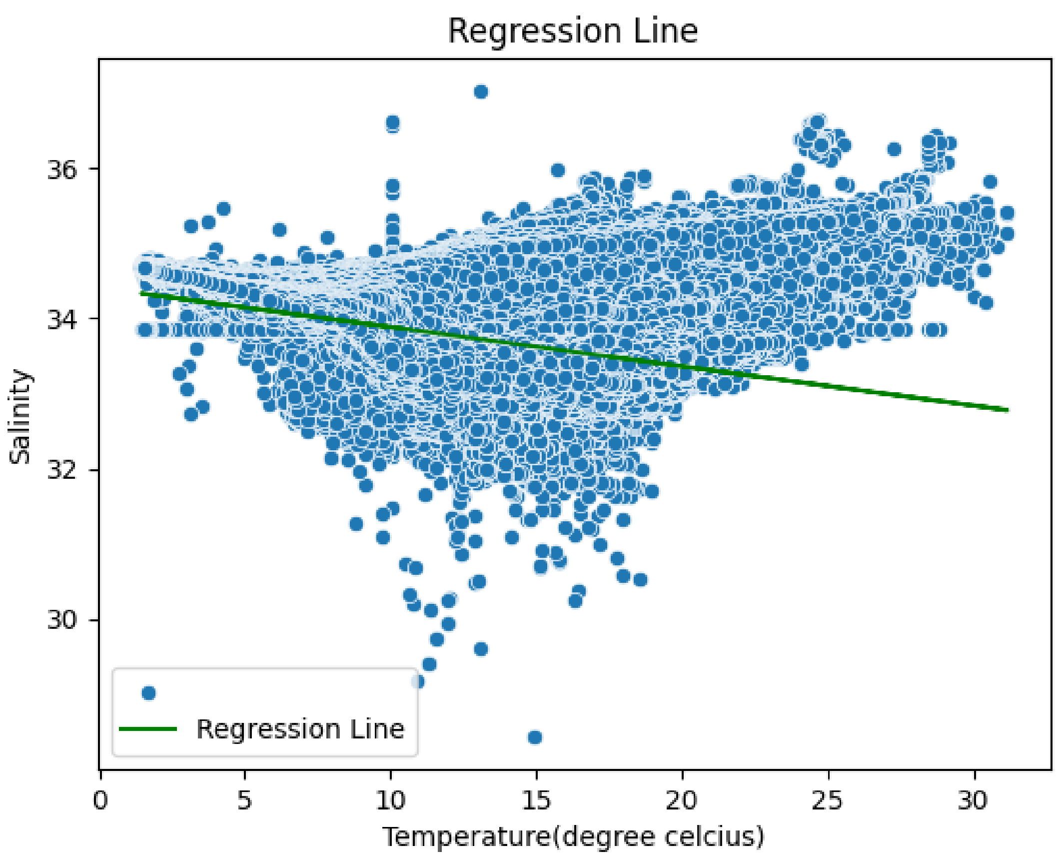

[233]:
```
x = data['T_degC']
y = m*x + c

sns.scatterplot(x = 'T_degC', y = 'Salnty', data = data)
plt.plot(x, y, color = 'green')
```

```
plt.title('Regression Line')
plt.ylabel('Salinity')
plt.xlabel('Temperature(degree celcius)')
plt.legend(['', 'Regression Line'])

r2 = r2_score(Y_test, Y_pred)
rmse = mean_squared_error(Y_test, Y_pred, squared = True)
print(f'R2 Score: {r2} \nRMSE : {rmse}')
```

```
R2 Score: 0.23655720111415657
RMSE : 0.15442077033266072
```

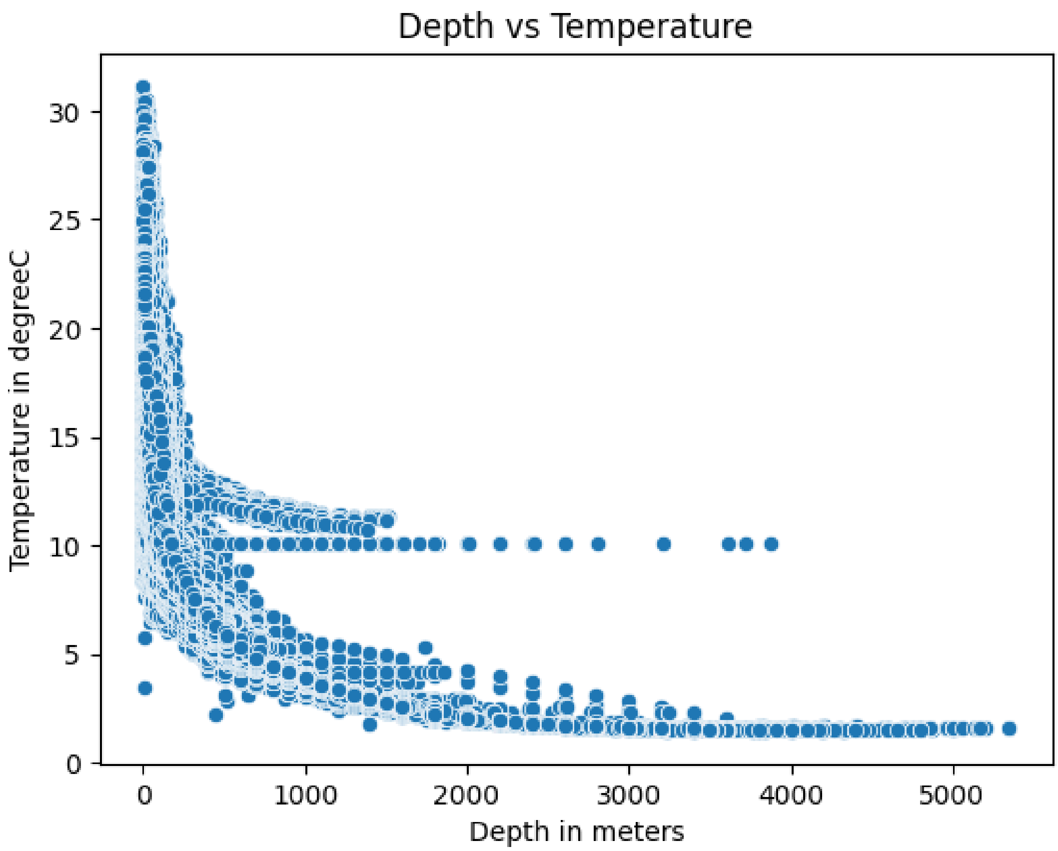



**RMSE from non scaled data shows that the standard deviation for prediction of salinity is only 0.15.**

### 5.0.2 Depth and Temperature

[236]:
```
sns.scatterplot(y = data['T_degC'], x = data['Depthm'], data = data)
plt.title('Depth vs Temperature')
plt.xlabel('Depth in meters')
plt.ylabel('Temperature in degreeC')
```

[236]: Text(0, 0.5, 'Temperature in degreeC')




Scatterplot between Depth and Temperature shows that there is no linear relation between them but there is a polynomial relationship. It clearly shows temperature decreases with increasing depth in the ocean. Let's use Decision Tree Regressor to create a model to predict temperatures based on depth.

[18]:
```
from sklearn.tree import DecisionTreeRegressor
```

[ ]:
```
X = data['Depthm'].to_numpy().reshape(-1,1)
Y = data['T_degC'].to_numpy().reshape(-1,1)

dtr = DecisionTreeRegressor()
```

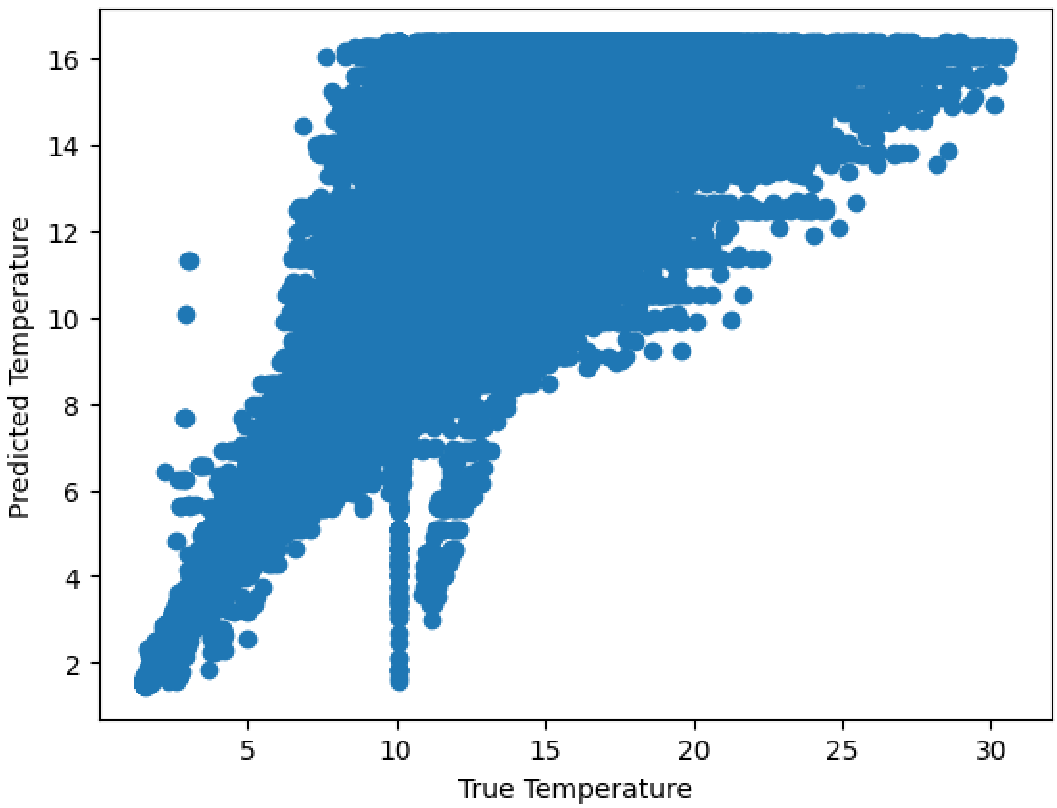
```
X_train,X_test,Y_train,Y_test = train_test_split(X, Y, test_size = 0.3)

dtr.fit(X_train,Y_train)
```

After fitting the Depth and Temperature data into decision tree regression models, we can now visualize how good the predictions this model can make.

[57]:
```
Y_pred = dtr.predict(X_test)
plt.scatter(Y_test,Y_pred)
plt.xlabel('True Temperature')
plt.ylabel('Predicted Temperature')
```

[57]:
```
Text(0, 0.5, 'Predicted Temperature')
```




We see a pretty linear graph that means we might have got a good score too. Let's evaluate scores and error metrics for the model.

[62]:
```
r2 = r2_score(Y_test, Y_pred)
rmse = mean_squared_error(Y_test, Y_pred, squared = True)
print(f'R2 Score: {r2} \nRMSE : {rmse}')
```

```
R2 Score: 0.771862007099797
RMSE : 4.066286864343186
```

This model got a score of 0.77 and RMSE value is 4.066. It means the predicted temperatures are within $\pm$ 4 degrees. That's a pretty good model to predict the temperature in the ocean given the depth.

## 6 Discussion and Conclusion

To conclude about any data project, we need to have a good understanding of the dataset, its collection procedures and the way it is analyzed. In the context of this project we must not forget that we had more than 70 variables out of which we selected and tried to establish some relation between salinity and temperature. The results show that there is not very strong correlation between temperature and salinity and the regression fit is also poor. The score of the regression is very less i.e. only 0.24. Though we got an insight from the analysis that there is negative correlation between temperature and salinity and also there is positive correlation between depth and salinity. To be able to predict Salinity we need to consider more variables.

In conclusion, the project is successful in answering the research questions. We can predict the salinity in the ocean given the temperature only with 23% accuracy . We can conclude that it is not possible to perfectly predict salinity from the temperature alone since there are a lot of other physical, biological and chemical factors affecting the salt levels in the ocean. But we can indeed conclude that there exists a negative correlation between salinity and temperature, i.e. with increasing temperature, salinity decreases and vice versa. Also in the case of depth and temperature, temperature decreases as depth increases in the ocean. We can predict the temperature in the ocean given the depth with 77% accuracy .