```
In [1]: %%capture
        # Install the autograder to check your answers as you go along
        import sys
        !{sys.executable} -m pip install otter-grader
        # Initialize Otter
        import otter
        grader = otter.Notebook("HW4.ipynb")
        import warnings
        warnings.filterwarnings("ignore")
```

1 Homework #4

Due Friday Dec. 1st @ 11:59 pm

Objective: This assignment synthesizes many data analysis and plotting skills you have learned this quarter including reading text files, Numpy, Pandas, SciPy, and plotting.

1.1 Instructions:

1.1.1 Accessing Class Code

1. Clone this repository into your own JupyterHub by running this command in your home directory: `git clone your_SSH_URL`
2. Once you have cloned the repository, go into your directory and set your branch to "main" (See the GitHub cheatsheet for help on this). You will not need to reset your remote origin, as you have already directly cloned from your own version of the repository.
3. There should now be a "homework_4" directory in the home directory of your JupyterHub. In terminal, change directories into "homework_4". Next, click on the the "homework_4" icon on the filepath hierarchy in the left panel of JupyterHub. If you don't see it, make sure you're in the home folder by clicking the folder icon under the search bar.
4. Double click the "HW4.ipynb" to open it in a new tab and begin working on the assignment. Read the instructions carefully, and make sure to write your answers in the specified cells. Typically, you will see a "…" in the places you need to fill in. Make sure to use the variable names provided in the starter code. See the "Working in your Notebook" section below for an example. There are some autograder tests embedded in the notebook, but there are also some hidden tests that will be graded after submission.
5. Edit the README file and write your name and UW NetID. Include a paragraph on some advantages and disadvantages of smoothing data by linear regression, interpolation, or rolling means (4-5 sentences. Review the week 8-9 pre-lectures for review on these methods. (5 points)
6. As you continue to answer the homework questions and make edits to your code, make sure to regularly update your GitHub repository as well via git add, commit, and push (steps 15, 16, 19 in 0b). A good rule of thumb would be to run these git steps anytime you make an addition or change that you

don't want to accidentally lose. Generally, you can push once a day to maintain good version control practices. As a note, make sure that your git commands are running without errors before you refresh your GitHub and check your changes. If you are not seeing the updated changes you created in your local JupyterHub directory, check where your status is by this command: `git status`

Then, you can see if you made an error with your git add, commit, or push commands.

Sometimes, our JupyterHub server has trouble remembering the file permissions for our SSH keys. If you get a file permission error with your private ssh key, run this line of code: `chmod 400 ~/.ssh/id_ed25519`

This will change your file permission to the proper permissions that SSH requires.

1.1.2 Submitting to GradeScope

7. Go to the class Gradescope dashboard and submit your personal GitHub repository link to the Homework 2 assignment. Make sure your GitHub is synchronized with Gradescope to access both your public *and* private repositories. If prompted, log in to GitHub.
8. Run the autograder to check if your code runs and if you passed the initial unit tests. You should be able to run the autograder as many times as you want before submitting. Again, double check that your final answers are stored in the provided variable names given in the starter code!
9. Once the autograder has finished running, check that you have submitted the assignment. If you make any more changes to your code after submitting to Gradescope, make sure to push your changes to GitHub and resubmit the assignment on Gradescope. You can submit as many times as you want as there is no maximum submission attempts, but be sure to have your final submission in before the deadline.

1.1.3 Working in your Notebook

To help you start thinking about how to write meaningful and concise variable names, we have provided variable names in most of your questions. Note that there is an ellipsis (the "…") after each of the variable names. These are the sections you are expected to fill in. Please use the provided variable names (ie "pelagic" and "coastal" in the above example) to report your final answer back in. This will ensure that the autograder on Gradescope runs properly. Make sure that you are adding comments and your outside references as you go along! Part of your grade will include using best coding practices in your homework assignments.

1.1.4 Honor Code

- Complete the assignment by writing and executing text and code cells as specified. For this assignment, do not use any features of Python that have not yet been discussed in the lessons or class sessions.

- Please keep in mind our late work and dropped homework grading policy. Review the syllabus for details.
- You can acknowledge and describe any assistance you've received on this assignment in the specified cell of this HW3 notebook, whether that was from an instructor, classmate (either directly or on Ed Discussion), and/or online resources other than official Python documentation websites like docs.python.org or numpy.org. Alternatively, if you prefer, you may acknowledge assistance at the relevant point(s) in your code using a Python comment (#). Don't forget that you can receive extra credit from answering at least one question on Ed Discussion!

1.2 Required Plot Elements:

1. x and y axis labels with units
2. a meaningful, descriptive title
3. font size above 12

2 Grade Breakdown

- Question 1: 85 points
  - Part 1: 20 points
  - Part 2: 10 points
  - Part 3: 15 points
  - Part 4: 20 points
  - Part 5: 20 points
- Best coding practices: 10 points
- README: 5 points

Total: 100 points

- Extra Credit: 5 points for answering a question on Ed Discussion

3 Q1: Pakistan Sea Level Trends (85 points)

Threats from climate change often impact devloping countries most harshly. This is particularly true for nations at risk from sea level rise. Much of Pakistan is very low elevation, and the coastal city of Karachi is on average only 8 meters above sea level. Through a combination of sea level rise and river delta subsidence, some researchers estimate that Karachi could be underwater in the next several decades (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7517073/).

In this exercise, we will analyze sea level data curated by the Permanent Service for Mean Sea Level (https://psmsl.org/data/obtaining/stations/204.php). Data was collected intermittently from Karachi during 1910-2016 (graph from PSMSL below). We will explore how to best visualize this data and interpolate missing values. Finally, we will calculate the rate of sea level rise at Karachi.

3.1 Part 1: Reading in initial data and cleaning (20 points)

1) Use the `readline()` function and a for loop, find out how many lines of header are in the "Pakistan_sea_level_psmsl.txt" file and store this number in the `header_lines` variable. Read the information in the header. In this data file, missing sea level data points are filled with a placeholder "masking" value. (5 points) >1) What is the masking value for missing data in this dataset? Answer this question in the markdown cell below the solution cell.

2) Use numpy `genfromtext()` to read each column of your text file into a Numpy array as floats and store the array in the `sea_level` variable.(*HINT: Remember that indexing starts with 0 in Python!*). Store the columns as individual 1-D arrays (excluding "number of missing days") in the provided answer variables, `year_month`, `depth_mm`, `data_flag`. (5 points) >1) What is the delimiter type for this text file? Answer this question in the markdown cell below the solution cell.

3) Using the numpy `where()` function and its first positional argument (Documentation), find the indices of the masked depth values that represent missing values in your Numpy array and store the resulting array in `mask_inds`. Using `mask_inds`, replace the masking values in `depth_mm` with `np.nan` values. (5 points)

4) PSMSL also flags data that is likely erroneous. In this data, a data quality flag value of 11 represents bad data. We will also replace these suspicious values with `np.nan` values to ignore them. (5 points)

   a) Find the indices of bad data quality values in `data_flag` by numpy `where()` and store in `bad_inds`.

   b) Save the corresponding "year" and "depth_mm" values of bad data in a separate arrays, `bad_years` and `bad_depths` respectively.

   c) Replace bad depth values in `depth_mm` with `np.nan` values.

In [2]:
```python
# import the necessary packages
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from scipy import interpolate
from scipy import stats
print("Part 1")
# store filepath to data here
filepath = 'Pakistan_sea_level_psmsl.txt'
```

```python
    # open file path here
    fileobj = open(filepath, 'r')

    # Find how many lines of headers with readline()
    for i in range (30):
        line= fileobj.readline()
        print(line)
    fileobj.close()
    # store number of header_lines here
    header_lines = 22

    print("Part 2")
    #Make np array of data using genfromtext here
    sea_level = np.genfromtxt(filepath, skip_header=22, dtype=float, delimiter=';')

    #display
    display(sea_level)

    # store decimal years 1D array here
    year_month = sea_level[:,0]
    # store depth 1D array here
    depth_mm = sea_level[:,1]
    # store data flag 1D array here
    data_flag = sea_level[:,3]

    print("Part 3")
    # store indices where depth_mm is equal to missing data masked value here
    mask_inds = np.where(depth_mm == -99999)
    # replace missing data mask values in depth_mm with Nans
    depth_mm[mask_inds] = np.nan

    print("Part 4")
    # store indices of bad data values here
    bad_inds = np.where(data_flag == 11)
    # store years of bad data here
    badyears = year_month[bad_inds]

    # store depth values of bad data here
    baddepths = depth_mm[bad_inds]

    print(baddepths)
    # replace bad data values in depth_mm with Nans
    depth_mm[bad_inds] = np.nan

    ## Helped in this section by Roy
```

```
Part 1
Monthly sea level measurements from PSMSL

Station 204 Karachi, Pakistan

https://psmsl.org/data/obtaining/stations/204.php
```

Station ID: 204

Latitude: 24.811667

Longitude: 66.975

GLOSS ID: 30

Coastline code: 490

Station code: 21

Country: PAKISTAN

Time span of data: 1916 - 2016

Completeness (%): 57

MTL Data: 1937-1948

MTL-MSL (mm): 10

Date of last update: 30 Nov 2017

If there is a missing month in the data, the gap is padded with a mean sea level value of -99999.

Year and decimal month; Depth (mm); number of missing days; quality flag

1916.0417; 7021; 0;000

1916.1250; 6924; 0;000

1916.2083; 7000; 0;000

1916.2917; 7021; 0;000

1916.3750; 7015; 0;000

1916.4583; 7113; 0;000

1916.5417; 7134; 0;000

1916.6250; 7033; 0;000

```
Part 2
```

```
array([[1.9160417e+03, 7.0210000e+03, 0.0000000e+00, 0.0000000e+00],
       [1.9161250e+03, 6.9240000e+03, 0.0000000e+00, 0.0000000e+00],
       [1.9162083e+03, 7.0000000e+03, 0.0000000e+00, 0.0000000e+00],
       …,
       [2.0167083e+03, 7.1570000e+03, 4.0000000e+00, 0.0000000e+00],
       [2.0167917e+03, 7.1950000e+03, 4.0000000e+00, 0.0000000e+00],
       [2.0168750e+03, 7.2850000e+03, 0.0000000e+00, 0.0000000e+00]])
```

```
Part 3
Part 4
[6951. 7024. 7039. 7109. 7088. 7283. 7085. 7033. 6926. 6905. 6917. 6832.]
```

Type your answers to the question from Part 1 here 1A. The masking indicies value is -99999

2A. The Delimiter for this type of file is ;

```
In [3]: grader.check("Question 1, Part 1")
```

```
Out[3]: Question 1, Part 1 results: All test cases passed!
```

3.2 Part 2: Plotting (10 points)

5) Make a matplotlib figure with using plt.subplots(). *Make sure you include all required elements including proper labels, colors, and legends.*

   a) Plot your depth timeseries (x = `year_month`, y = `depth_mm`). Add a marker.

   b) Plot the bad depths you removed from your original arrays on the top subplot in a different color.

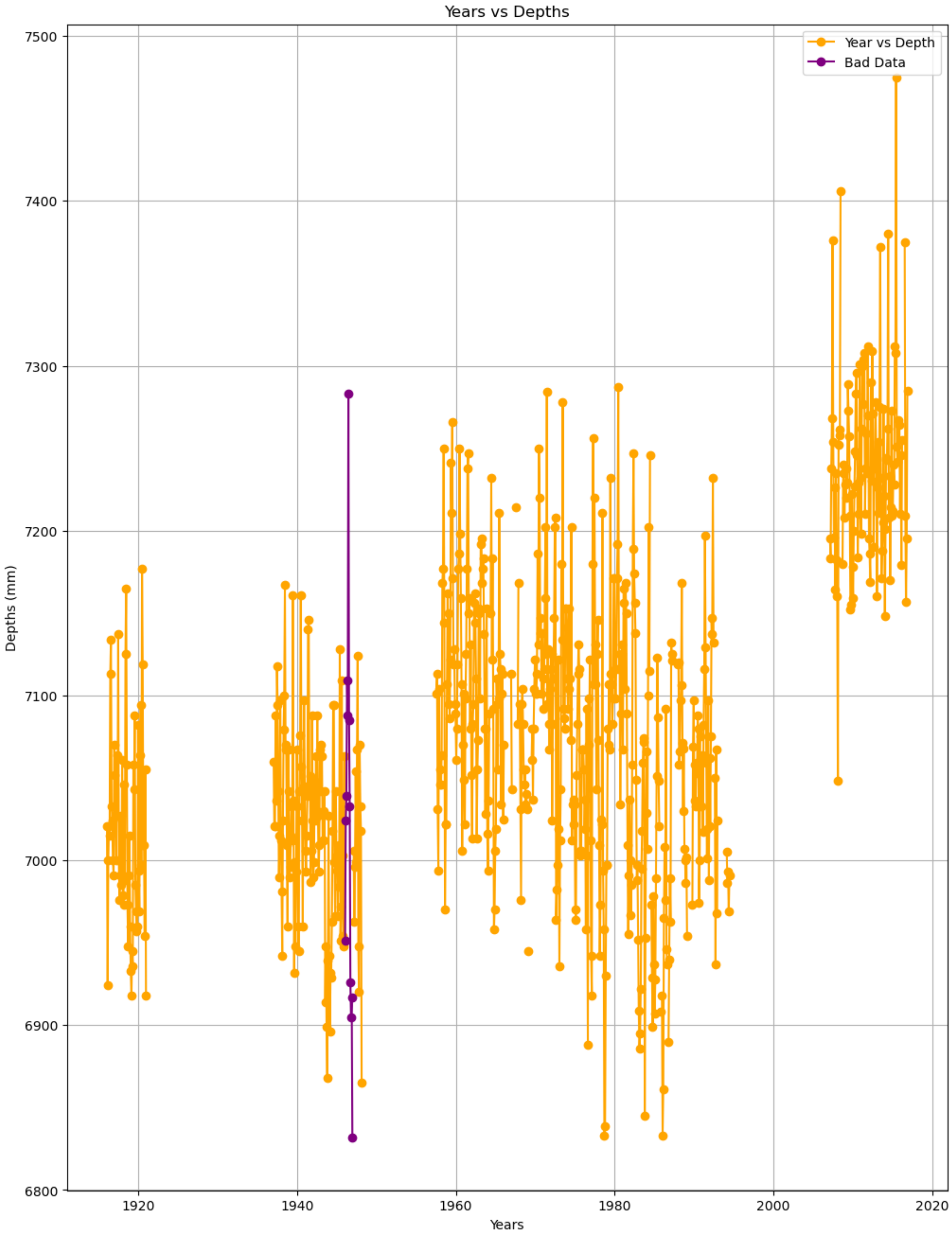
   c) Add a legend.

```
In [4]: print("Part 5")
        import matplotlib.pyplot as plt
```

```python
# create plot using subplots
plt.subplots(figsize=(12,16))
# plot year vs. depth
plt.plot(year_month, depth_mm, marker ='o', color ='orange', label = 'Year vs Depth')
# plot bad years vs. bad depths
plt.plot(badyears,baddepths,marker='o', color = 'purple', label = 'Bad Data')

# don't forget your required plot elements!
plt.xlabel('Years')
plt.ylabel('Depths (mm)')
plt.legend()
plt.grid()
plt.title('Years vs Depths')
```

Part 5

```
Out[4]: Text(0.5, 1.0, 'Years vs Depths')
```


Years vs Depths
Year vs Depth
Bad Data
Depths (mm)
Years
7500
7400
7300
7200
7100
7000
6900
6800
1920
1940
1960
1980
2000
2020

3.3 Part 3: Interpolation (15 points)

6) Turn your Numpy arrays into a DataFrame with three columns. (5 points)

   a) Store your `year_month`, `depth_mm`, and `data_flag` arrays in a list and transpose the list of arrays. Store this in the `list_data` variable.

   b) Create a pandas dataframe and set it as the variable `df`. Set the named argument, data=list_data, in the pandas `DataFrame()`.

   c) Set your column names to 'Year', 'Depth', and 'Flag' using the "columns" argument in the `DataFrame()` function.

   d) Display `df`.

7) There are large gaps in this dataset. Use Scipy's interp1d() to linearly interpolate the missing depth values. (5 points)

   a) Using the numpy `where()` function in the same was at Part 1.3, find the indices of depth values that are ***not*** `np.nan` using the df["Depth"] column. (**HINT: Use the pandas notnull() function**). Store these indices in the `depth_inds` variable.

   b) Build and store your interpolation function in `func`. Make sure to subset `df` by `depth_inds` when setting x as the 'Year' column of `df` and y as the 'Depth' column. Set the "kind" argument to "linear".

   c) Apply your interpolation function to all years in `df` to find interpolated depths. Store your interpolated depth values in a new column called "Depth_interp" in `df`.

   d) Display `df`.

8) Plotting the interpolated data and compare against original data. (5 points)

   a) Make a matplotlib figure with two subplots using the 'subplots()' function (set nrows = 2). Set the figsize to (10,6). **Make sure you include all required elements including proper labels, colors, and legends.**

b) Copy and paste your plot from Part 2) onto the **top** subplot. Include the depth time series and bad depth values, and make sure to plot on the correct axes object.

c) Plot the "Depth_interp" values on your bottom subplot as a different color from your "Depth" data. Add a label and make a legend for the **bottom** subplot.

d) Do you think the interpolation accurately describes trends in missing depth data? Why or why not? Answer this question in the markdown cell below the code solution cell.

In [32]:
```
## Part 6
print('Part 6: ')
# store arrays into list and transpose here
list_data = [year_month, depth_mm, data_flag]
list_data = np.array(list_data).T
# Make a Dataframe with list_data, and set Year, Depth, and Flag as column names
df = pd.DataFrame(data = list_data, columns = ['Year', 'Depth', 'Flag'])
# display your dataframe
display(df)

print('Part 7: ')
# find the indices where df["Depth"] is not null and store here
depth_inds = np.where(df['Depth'].notnull())
# linearly interpolate missing data
x = df.loc[depth_inds,'Year'] # setting the variables as x and y helps me think about how i am
y = df.loc[depth_inds,'Depth']
func = interpolate.interp1d(x,y, kind = 'linear', bounds_error = False, fill_value='extrapolate
# make new "Depth_interp" column in df here
df['Depth_interp'] = func(df['Year'])
# display your dataframe here
display(df['Depth_interp'])

print('Part 8: ')
# plot figure with 2 subplots below
fig, axs = plt.subplots(figsize = (10,6), nrows=2, sharex = False)
# copy and paste code from part 1) into top subplot

# ok so that didn't work, so instead i stole the code from 11/21/23 coding demo and it looks l
axs[0].plot(year_month, depth_mm, marker ='o', color ='orange', label = 'Year vs Depth')
axs[0].set_xlabel('Year')
axs[0].set_ylabel('Depth')
axs[0].legend()

#plot Year vs. Depth_interp in bottom subplot
axs[1].plot(year_month, df['Depth_interp'], marker ='o',color='blue', label = 'Depth Interpola
axs[1].set_xlabel('Year')
axs[1].set_ylabel('Depth')
axs[1].legend()
```

```
Part 6:
```

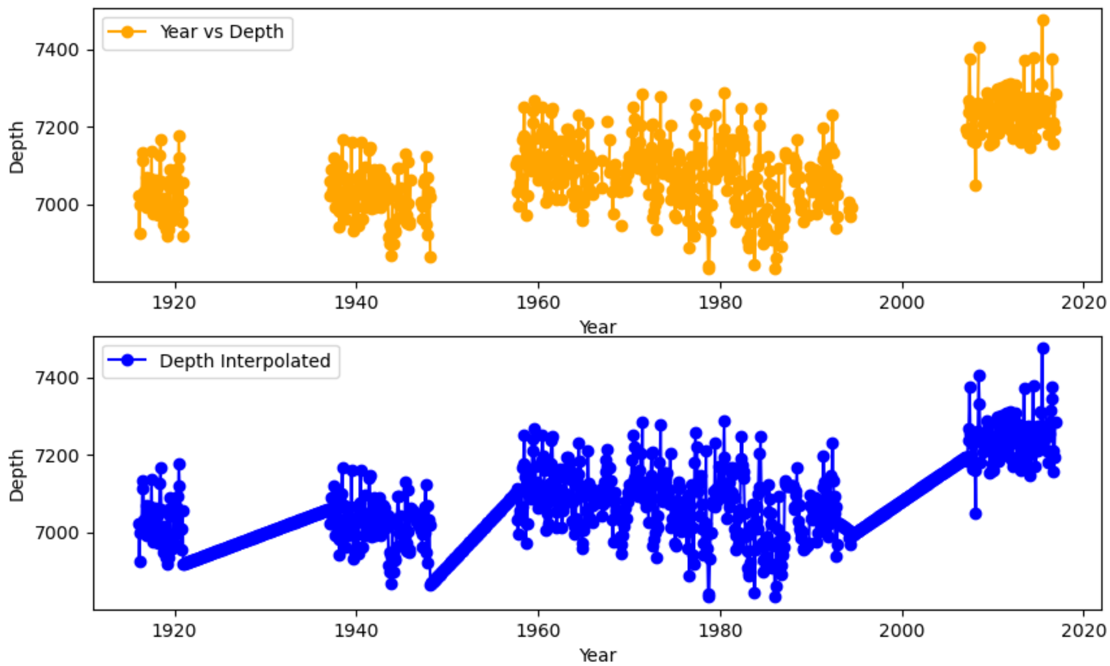
```
            Year   Depth  Flag
0     1916.0417  7021.0   0.0
1     1916.1250  6924.0   0.0
2     1916.2083  7000.0   0.0
3     1916.2917  7021.0   0.0
4     1916.3750  7015.0   0.0
…           …       …    …
1206  2016.5417  7375.0   0.0
1207  2016.6250  7209.0   0.0
1208  2016.7083  7157.0   0.0
1209  2016.7917  7195.0   0.0
1210  2016.8750  7285.0   0.0

[1211 rows x 3 columns]
```

Part 7:

```
0       7021.0
1       6924.0
2       7000.0
3       7021.0
4       7015.0
         …
1206    7375.0
1207    7209.0
1208    7157.0
1209    7195.0
1210    7285.0
Name: Depth_interp, Length: 1211, dtype: float64
```

Part 8:

```
Out[32]: <matplotlib.legend.Legend at 0x7fbd8ad971f0>
```



Type your answers to the question from Part 3 here 8d.

```
In [6]: grader.check("Question 1, Part 3")
```

```
Out[6]: Question 1, Part 3 results: All test cases passed!
```

3.4 Part 4: Calculate Rolling Mean and Interpolate (20 points)

9) Depth data varies greatly between months, which can make it difficult to see larger scale trends. (10 points)

   a) To better visualize yearly trends, calculate the rolling yearly mean of depths using Pandas function `.rolling()` function (Documentation). *HINT: The data is in monthly resolution. How many months will you need to get the rolling yearly mean?*

   b) Store the rolling mean depth values in a new column called "yearly_height" in `df`.

   c) Copy and paste your plot from Part 8).

d) Plot your "yearly_height" values against "Year" on the **top** subplot, overlaying the original time series data. Make this line a different color and line style, and add it to the legend in the top subplot.

10) The .rolling() function does not deal with nan values, which represents our missing and suspicious data. This results in creating larger data gaps in the calculated rolling mean depth values compared to the original data. Here, we will *interpolate and extrapolate* the rolling mean values to resolve the data gaps. (10 points)

    a) Using the numpy `where()` function in the same was at Part 3.7, find the indices of depth values that are ***not*** `np.nan` using the df["yearly_height"] column. Store these indices in the `rolling_inds` variable.

    b) Build and store your interpolation function in `func` as you did in part 3.7. Make sure to subset `df` by `rolling_inds` when setting x as the 'Year' column of `df` and y as the 'yearly_height' column. Set the "kind" argument to "linear" again, and also use the named argument: fill_value="extrapolate".

    c) Store your interpolated rolling mean depth values in a new column called 'Depth_interp_roll' in `df`.

    d) Building off your plot from Part 9, plot your interpolated rolling mean depth values ('Depth_interp_roll') on your **bottom** subplot. Add it to the legend in the bottom subplot. (You do not need to copy/paste the code here, just add the line of code underneath your plotting code from Part 9).

    e) Do you think this interpolation describes the trends in missing depth data more or less accurately than your first interpolation attempt? Why or why not? Store your answer in the markdown cell below the solution cell.

Type your answer here, replacing this text.

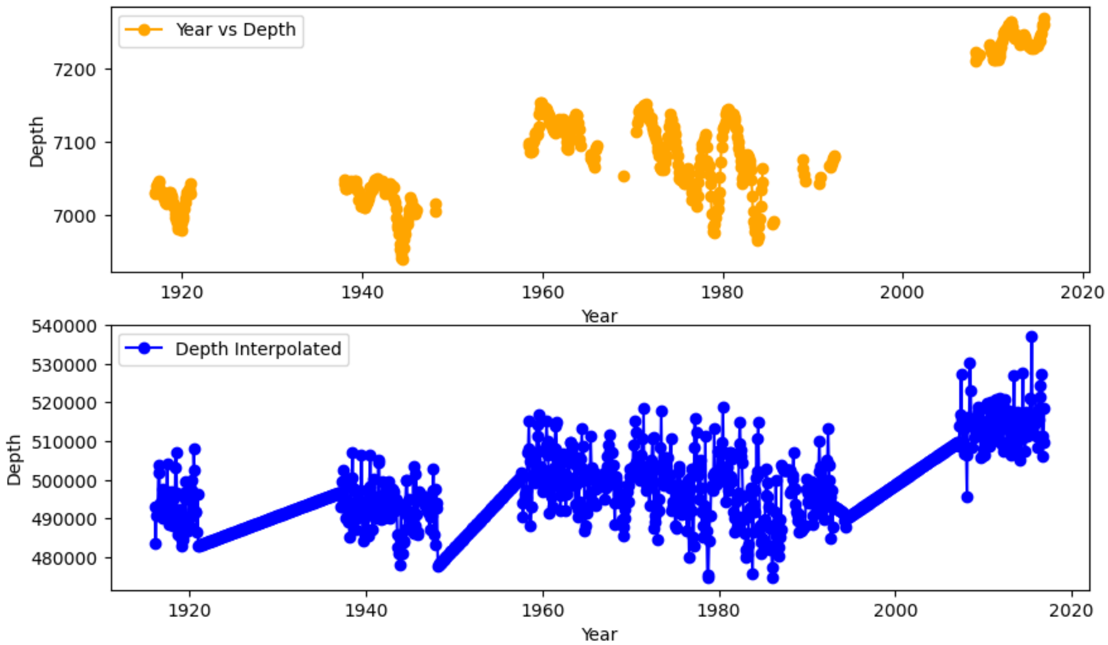
In [27]:
```
print('Part 9: ')
# Use pandas .rolling to get yearly averages of sea level and store in a new column called 'ye
y_h = df['Depth'].rolling(window=12).mean()
#print(y_h)
df['yearly_height']=y_h
print('Part 10: ')
# find the indices where df["yearly_height"] is not null and store here
rolling_inds = np.where(df['yearly_height'].notnull())
# linearly interpolate missing data
xx = df.loc[rolling_inds,'Year'] #again, setting variables helps me process information in my
yy=df.loc[rolling_inds,'yearly_height']
```

```python
        func = interpolate.interp1d(xx,yy, kind = 'linear',bounds_error=False, fill_value="extrapolate
        # make new "Depth_interp_roll" column in df here
        df['Depth_interp_roll'] = func(df['Depth_interp'])
        # display your df dataframe here
        display(df)

        ## plot figure with yearly interpolated depth and rolling interpolated depth
        # copy and paste code from part 8)
        fig, axs = plt.subplots(figsize = (10,6), nrows=2, sharex = False)
        # plot Year vs. yearly_height in top subplot
        axs[0].plot(year_month, df['yearly_height'], marker ='o', color ='orange', label = 'Year vs De
        axs[0].set_xlabel('Year')
        axs[0].set_ylabel('Depth')
        axs[0].legend()
        # plot Year vs. Depth_interp_roll in bottom subplot
        axs[1].plot(year_month, df['Depth_interp_roll'], marker ='o',color='blue', label = 'Depth Inte
        axs[1].set_xlabel('Year')
        axs[1].set_ylabel('Depth')
        axs[1].legend()
```

```
Part 9:
Part 10:
```

```
           Year   Depth  Flag  Depth_interp  full_regression
0     1916.0417  7021.0   0.0        7021.0      6962.827528  \
1     1916.1250  6924.0   0.0        6924.0      6962.990601
2     1916.2083  7000.0   0.0        7000.0      6963.153675
3     1916.2917  7021.0   0.0        7021.0      6963.316945
4     1916.3750  7015.0   0.0        7015.0      6963.480019
…           …       …   …           …                …
1206  2016.5417  7375.0   0.0        7375.0      7159.573380
1207  2016.6250  7209.0   0.0        7209.0      7159.736454
1208  2016.7083  7157.0   0.0        7157.0      7159.899528
1209  2016.7917  7195.0   0.0        7195.0      7160.062798
1210  2016.8750  7285.0   0.0        7285.0      7160.225872

      recent_regression  yearly_height  Depth_interp_roll
0           6898.826080            NaN      492976.827931
1           6899.123545            NaN      483564.062825
2           6899.421010            NaN      490939.012805
3           6899.718832            NaN      492976.827931
4           6900.016297            NaN      492394.595038
…                   …            …                …
1206        7257.712338            NaN      527328.568627
1207        7258.009803            NaN      511220.125250
1208        7258.307268            NaN      506174.106843
1209        7258.605090            NaN      509861.581833
1210        7258.902555            NaN      518595.075230

[1211 rows x 8 columns]
```

Out[27]: <matplotlib.legend.Legend at 0x7fbd8af65e70>



Type your answers to the question from Part 4 here 10e.

yes, it is a more accurate reprisentation of the data, because the rolling averages takes more continuous averages over the data than standard averages by month would do (better genearalization of the data)

```
In [8]: grader.check("Question 1, Part 4")
```

```
Out[8]: Question 1, Part 4 results: All test cases passed!
```

3.5 Part 5: Perform linear regression (20 points)

11) Model average sea level rise using a linear regression. (10 points)

    a) Calculate a linear regression using SciPy's `linregress()` function. Set x to "Year" and y to "Depth_interp"*. Do this in one line of code and store the output in the `slope`, `intercept`, `rvalue`, `pvalue`, and `stderr` variables.

*It is necesarry to use interpolated depth values because linregress does not work with `np.nan` values.

b) Use the `slope`, `intercept`, and your "Year" column to calculate the linear regression fit (Review group_activity7 or Week 8 pre-lecture slides if you forgot the formula). Store the linear regression fit as a new column called "full_regression" in `df`.

c) Copy and paste your plot from Part 4.9-4.10.

d) Plot your "full_regression" values against "Year" on the **bottom** subplot, overlaying the previous interpolated depth and rolling mean interpolation data. Make this line a different color and line style, and include the calculated rate of sea level rise (including units) in your plot legend.

e) Does a linear model accurately describe how depth is changing over time? Why? Type your answer in the markdown cell below the coding solution cell.

12) Investigate whether sea level rise has been accelerating over time. (10 points)

a) Make a new DataFrame including all columns from `df`, but subset the rows from the most recent instrumentation period ("Year" > 2007). Name it `recent_df`. *HINT: Use the `loc[]` function*

b) Design another linear regression as in part 11a using the "Depth_interp" column in `recent_df`. Store the output in the `slope_new`, `intercept_new`, `rvalue_new`, `pvalue_new`, and `stderr_new` variables.

c) Calculate the linear regression fit with `slope_new` and `intercept_new`, but use the "Year" column from `df`, ***not `recent_df`***. Store the recent regression fit as a new column called "recent_regression" in `df`.

d) Building off your plot from Part 11, plot your recent regression values ('recent_regression') on your **bottom** subplot. Add it to the legend in the bottom subplot and include the calculated rate of sea level rise (including units) in your plot legend. (You do not need to copy/paste the code here, just add the line of code underneath your plotting code from Part 11).

e) Compare the slopes of your two linear regressions. Do you think sea level rise is accelerating? Why or why not? Type your answer in the markdown cell below the coding solution cell.

Type your answer here, replacing this text.

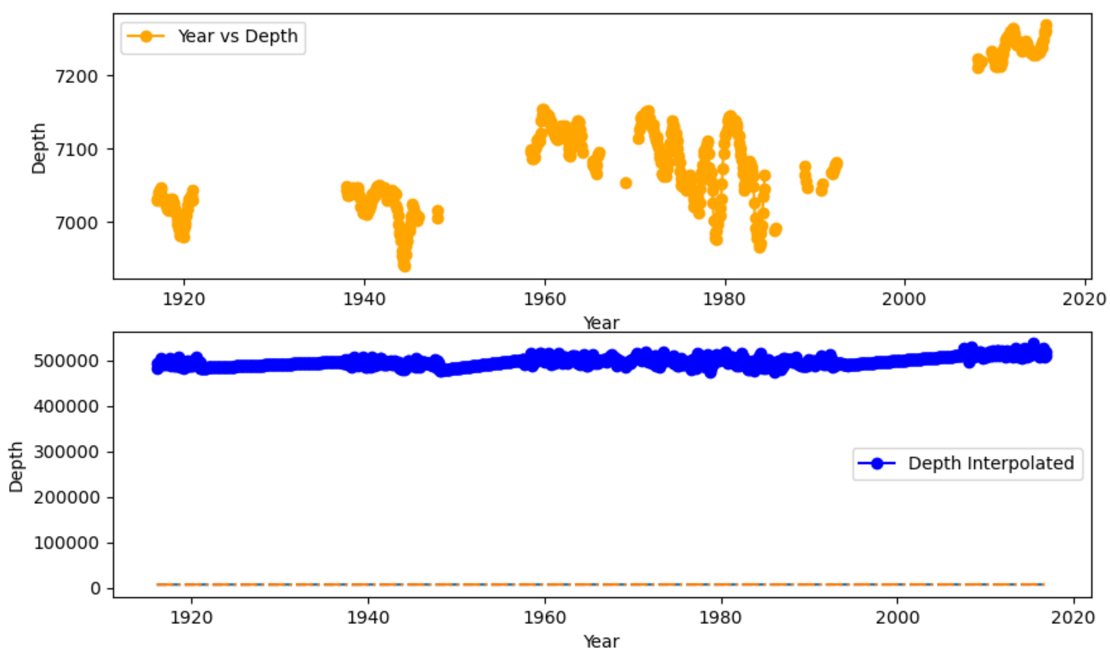
```
In [9]: #display(y)
```

```
In [31]: print("Part 11: ")
         # get linear regression terms, separated out in variables for my understanding
         xxx = df['Year']
         yyy = df['Depth_interp']
         slope, intercept, rvalue, pvalue, stderr = stats.linregress(xxx,yyy)
         print(slope)
         print(intercept)
         # calculate linear regression fit and store in full_regression column
         full_reg = slope*xxx + intercept
         df['full_regression'] = full_reg

         print("Part 12: ")
         # subset df past 2007 and store here
         recent_df = df.loc[df['Year']>2007]
         y_new = recent_df['Depth_interp']
         print(recent_df)
         # get linear regression terms for recent data
         slope_new, intercept_new, rvalue_new, pvalue_new, stderr_new = stats.linregress(recent_df['Yea
         # calculate linear regression fit and store in recent_regression column
         df['recent_regression'] = slope_new * xxx + intercept_new
         #display(recent_df)
         ## plot figure with regression values from full and recent datasets
         # copy and paste code from part 8)
         fig, axs = plt.subplots(figsize = (10,6), nrows=2, sharex = False)
         axs[0].plot(year_month, df['yearly_height'], marker ='o', color ='orange', label = 'Year vs Dep
         axs[0].set_xlabel('Year')
         axs[0].set_ylabel('Depth')
         axs[0].legend()
         # plot Year vs. full_regression in bottom subplot
         axs[1].plot(year_month, df['Depth_interp_roll'], marker ='o',color='blue', label = 'Depth Inte
         axs[1].plot(year_month, df['full_regression'], linestyle = '--')
         axs[1].set_xlabel('Year')
         axs[1].set_ylabel('Depth')
         axs[1].legend()
         # plot Year vs. recent_regression in bottom subplot
         axs[1].plot(year_month, df['recent_regression'], linestyle = '-.', label = 'Depth Interpolated
```

```
Part 11:
1.9576701742151223
3211.8498388807147
Part 12:
           Year   Depth  Flag  Depth_interp  full_regression
1092  2007.0417     NaN   0.0   7193.658435      7140.975513  \
1093  2007.1250  7195.0   0.0   7195.000000      7141.138587
1094  2007.2083  7183.0   0.0   7183.000000      7141.301661
1095  2007.2917  7238.0   0.0   7238.000000      7141.464931
1096  2007.3750  7268.0   0.0   7268.000000      7141.628005
…           …      …    …             …                …
1206  2016.5417  7375.0   0.0   7375.000000      7159.573380
```

```
1207  2016.6250  7209.0   0.0   7209.000000      7159.736454
1208  2016.7083  7157.0   0.0   7157.000000      7159.899528
1209  2016.7917  7195.0   0.0   7195.000000      7160.062798
1210  2016.8750  7285.0   0.0   7285.000000      7160.225872

      recent_regression  yearly_height  Depth_interp_roll
1092        7223.787766            NaN      509731.397965
1093        7224.085231            NaN      509861.581833
1094        7224.382696            NaN      508697.116046
1095        7224.680518            NaN      514034.250900
1096        7224.977983            NaN      516945.415366
…                 …              …                …
1206        7257.712338            NaN      527328.568627
1207        7258.009803            NaN      511220.125250
1208        7258.307268            NaN      506174.106843
1209        7258.605090            NaN      509861.581833
1210        7258.902555            NaN      518595.075230

[119 rows x 8 columns]
```

```
Out[31]: [<matplotlib.lines.Line2D at 0x7fbd8ad435e0>]
```



Type your answers to the question from Part 5 here 11e. While not perfect, a linear model can be used to see the general trends of increase and decrease over time for this data, because the increase and decrease shouldn't be exponential or quadratic (wel

12e.

```
In [ ]: grader.check("Question 1, Part 5")
```

3.6 Submission

Make sure you have run all cells in your notebook in order before running the cell below, so that all images/graphs appear in the output. The cell below will generate a zip file for you to submit. **Please save before exporting!**

After checking that all tests have passed, make sure to push your assignment to GitHub and submit to Gradescope. Do not upload the generated zip file to Gradescope unless you are having issues with GitHub and we have recommended you to do this.

```
In [ ]: # Save your notebook first, then run this cell to export your submission.
        grader.export(filtering=False, run_tests=True)
```