PART 1: Moving data into a dataframe and manipulating it

First, import libraries that we will use in this notebook

```
import numpy as np
import pandas as pd
```

```
from matplotlib import pyplot
from pandas import DataFrame
```

Now, we want to mount Google Drive to Colab to be able to read data from the CSV file

```
# Load the Drive helper and mount
from google.colab import drive

# This will prompt for authorization.
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Use unix ls command to make sure that the file we will load is on MyDrive

```
!ls drive/MyDrive/CstatWeatherNov19.csv
```

```
drive/MyDrive/CstatWeatherNov19.csv
```

Insert a code cell below this one that contains code to import the csv data from the file into a dataframe df using Pandas read_csv -- note that if you use interational charactersets, sometimes these can fail during read_csv(). Often including encoding = 'unicode_escape' in the read_csv() fixes this problem.

```
df = pd.read_csv('/content/drive/MyDrive/CstatWeatherNov19.csv')
```

Use info() to look at the number and types of data that we loaded into the dataframe. Here we use the "dot notation." Dot notation allows us to refer to method of the object (method is a function exclusive to a specific class/object/instance) or attribute of the instance/object. Methods have () at the end of the name, attributes do not. So here's the info() method for the dataframe df:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Day              30 non-null     object
 1   high degree F    30 non-null     float64
 2   low degree F     30 non-null     float64
 3   Precip inch      30 non-null     object
 4   Snow inch        30 non-null     int64
 5   snow depth inch  30 non-null     int64
dtypes: float64(2), int64(2), object(2)
memory usage: 1.5+ KB
```

Python machine learning tools that we will use extensively operate on numeric data. We have Day which is an object type and Precip inch (rainfall data) is currently an object type.

Let's look at the first few rows of the dataframe:

```
df.head()
```

	Day	high degree F	low degree F	Precip inch	Snow inch	snow depth inch
0	11/1/2019	63.0	32.0	0	0	0
1	11/2/2019	71.1	39.0	0	0	0
2	11/3/2019	73.0	42.1	0	0	0
3	11/4/2019	80.1	53.1	0	0	0
4	11/5/2019	84.9	64.0	0	0	0

Next steps: Generate code with df New interactive sheet

First, convert Day into a special type which will allow us to do date/time manipulations using Pandas to_datefime()

```
df['Day'] = pd.to_datetime(df['Day'], format = '%m/%d/%Y')
```

Now insert a cell to check the info() again

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Day              30 non-null     datetime64[ns]
 1   high degree F    30 non-null     float64
 2   low degree F     30 non-null     float64
 3   Precip inch      30 non-null     object
 4   Snow inch        30 non-null     int64
 5   snow depth inch  30 non-null     int64
dtypes: datetime64[ns](1), float64(2), int64(2), object(1)
memory usage: 1.5+ KB
```

Next, Precip inch. Look at the values for precipitation to see why they are objects.

```
df['Precip inch']
```

	Precip inch
0	0
1	0
2	0
3	0
4	0
5	0
6	0.11
7	0.02
8	0
9	0
10	0.19
11	0.01
12	T
13	0.62
14	0
15	0
16	0
17	0
18	0
19	0.01
20	0.13
21	0.08
22	0
23	0
24	T
25	0
26	T
27	0.03
28	0.07
29	T

dtype: object

The use of T for trace rainfall is causing the problem. Trace means that detectible precipitation of less than 0.005 inches were detected. For simplicity, substitute a small number for T. Note: trace in snow depth is defined as less than 0.05 inches

```
df.loc[df['Precip inch']=='T', ['Precip inch']] = 0.005
```

Now, we've eliminated the Ts, but that doesn't automatically change the Dtype. Change the Dtype to float

```
df['Precip inch'] = df['Precip inch'].astype(float, errors = 'raise')
```

Again, insert a cell and use info() to check the type is now numeric

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   Day              30 non-null     datetime64[ns]
 1   high degree F    30 non-null     float64
 2   low degree F     30 non-null     float64
 3   Precip inch      30 non-null     float64
 4   Snow inch        30 non-null     int64
 5   snow depth inch  30 non-null     int64
dtypes: datetime64[ns](1), float64(3), int64(2)
memory usage: 1.5 KB
```

So, look at all the cleaned data. Since this is a small dataframe we can look at it all at once. For large datasets, use df.head() to show the first 5 rows. df.tail(7) will show the last 7 rows in the dataframe. Experiement with these in the next few cells. Try the entire dataframe, then the first 5 rows and the last 7 rows

```
df
#df.head()
#df.tail(7)
```

	Day	high degree F	low degree F	Precip inch	Snow inch	snow depth inch
0	2019-11-01	63.0	32.0	0.000	0	0
1	2019-11-02	71.1	39.0	0.000	0	0
2	2019-11-03	73.0	42.1	0.000	0	0
3	2019-11-04	80.1	53.1	0.000	0	0
4	2019-11-05	84.9	64.0	0.000	0	0
5	2019-11-06	84.9	64.0	0.000	0	0
6	2019-11-07	70.0	46.9	0.110	0	0
7	2019-11-08	54.0	45.0	0.020	0	0
8	2019-11-09	69.1	42.1	0.000	0	0
9	2019-11-10	77.0	45.0	0.000	0	0
10	2019-11-11	75.9	35.1	0.190	0	0
11	2019-11-12	46.0	30.9	0.010	0	0
12	2019-11-13	45.0	28.0	0.005	0	0
13	2019-11-14	46.0	37.0	0.620	0	0
14	2019-11-15	64.0	34.0	0.000	0	0
15	2019-11-16	64.0	34.0	0.000	0	0
16	2019-11-17	70.0	42.1	0.000	0	0
17	2019-11-18	73.0	46.0	0.000	0	0
18	2019-11-19	80.1	46.9	0.000	0	0
19	2019-11-20	82.9	57.9	0.010	0	0
20	2019-11-21	80.1	70.0	0.130	0	0
21	2019-11-22	71.1	48.9	0.080	0	0
22	2019-11-23	64.9	44.1	0.000	0	0
23	2019-11-24	72.0	39.9	0.000	0	0
24	2019-11-25	82.9	48.9	0.005	0	0
25	2019-11-26	79.0	66.0	0.000	0	0
26	2019-11-27	71.1	54.0	0.005	0	0
27	2019-11-28	63.0	53.1	0.030	0	0
28	2019-11-29	79.0	55.9	0.070	0	0
29	2019-11-30	86.0	62.1	0.005	0	0

Next steps: Generate code with df New interactive sheet

```
#df
df.head()
#df.tail(7)
```

	Day	high degree F	low degree F	Precip inch	Snow inch	snow depth inch
0	2019-11-01	63.0	32.0	0.0	0	0
1	2019-11-02	71.1	39.0	0.0	0	0
2	2019-11-03	73.0	42.1	0.0	0	0
3	2019-11-04	80.1	53.1	0.0	0	0
4	2019-11-05	84.9	64.0	0.0	0	0

```
#df
#df.head()
df.tail(7)
```

	Day	high degree F	low degree F	Precip inch	Snow inch	snow depth inch
23	2019-11-24	72.0	39.9	0.000	0	0
24	2019-11-25	82.9	48.9	0.005	0	0
25	2019-11-26	79.0	66.0	0.000	0	0
26	2019-11-27	71.1	54.0	0.005	0	0
27	2019-11-28	63.0	53.1	0.030	0	0
28	2019-11-29	79.0	55.9	0.070	0	0
29	2019-11-30	86.0	62.1	0.005	0	0

This dataframe is quite clean. We could do some additional things like fixing consistency of capitalization of the feature names. df.rename() would change the column names.

Instead, lets work on a dirty data example.

This file DataClean.csv is on canvas. Insert some cells that: Go get the file, make sure it is in your MyDrive directory, and read it into a dataframe named dirtydf (following what we did above for the weather data.)

```
#verify the file exists
!ls drive/MyDrive/DataClean.csv
```

```
drive/MyDrive/DataClean.csv
```

```
#load file into dataframe
dirtydf = pd.read_csv('/content/drive/MyDrive/DataClean.csv')
```

```
#see what it looks like
dirtydf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9 entries, 0 to 8
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Date      9 non-null      object 
 1   Gage 1    9 non-null      object 
 2   Gage 2    6 non-null      float64
 3   Gage 3    8 non-null      float64
 4   Gage 4    1 non-null      float64
 5   Measurer  9 non-null      object 
dtypes: float64(3), object(3)
memory usage: 564.0+ bytes
```

This dataframe is a MESS. Each feature (column) should have 9 observations or instances (rows). Let's take a look

```
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Gage 4	Measurer
0	10/1/2021	14.21	17.12	11.55	NaN	Ping
1	10/2/2021	14.08	NaN	11.04	9.6	Kishav
2	10/3/2021	15.23	NaN	12.21	NaN	Bob
3	10/4/2021	14.42	17.26	11.75	NaN	Abe
4	10/5/2021	Out sick	NaN	NaN	NaN	Dr Lowe
5	10/6/2021	13.77	16331894.00	12.22	NaN	Bob
6	10/7/2021	14	17.76	13.10	NaN	Kishav
7	10/8/2021	14.1	16.88	12.90	NaN	Ping
8	10/9/2021	14.7	17.40	13.30	NaN	Abe

Next steps: Generate code with dirtydf New interactive sheet

We can use the dataframe count method to see how many values we have in our datrframe. NaN values are not counted in count(). Many are obviously missing.

```
dirtydf.count()
```

	0
Date	9
Gage 1	9
Gage 2	6
Gage 3	8
Gage 4	1
Measurer	9

dtype: int64

First, let's fix the Date object like we did before. Insert cell below and run the cell.

```
dirtydf['Date'] = pd.to_datetime(dirtydf['Date'], format = '%m/%d/%Y')
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Gage 4	Measurer
0	2021-10-01	14.21	17.12	11.55	NaN	Ping
1	2021-10-02	14.08	NaN	11.04	9.6	Kishav
2	2021-10-03	15.23	NaN	12.21	NaN	Bob
3	2021-10-04	14.42	17.26	11.75	NaN	Abe
4	2021-10-05	Out sick	NaN	NaN	NaN	Dr Lowe
5	2021-10-06	13.77	16331894.00	12.22	NaN	Bob
6	2021-10-07	14	17.76	13.10	NaN	Kishav
7	2021-10-08	14.1	16.88	12.90	NaN	Ping
8	2021-10-09	14.7	17.40	13.30	NaN	Abe

Next steps: Generate code with dirtydf New interactive sheet

Since we have only one reading on Gage 4, doing statistical analysis will not be very useful for this column. Let's just drop this entire column from our dataframe:

```
dirtydf = dirtydf.drop(['Gage 4'], axis=1) #many ways of specifying how to drop this column. Check out pandas documentation for oth
```

How does it look now

```
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Measurer
0	2021-10-01	14.21	17.12	11.55	Ping
1	2021-10-02	14.08	NaN	11.04	Kishav
2	2021-10-03	15.23	NaN	12.21	Bob
3	2021-10-04	14.42	17.26	11.75	Abe
4	2021-10-05	Out sick	NaN	NaN	Dr Lowe
5	2021-10-06	13.77	16331894.00	12.22	Bob
6	2021-10-07	14	17.76	13.10	Kishav
7	2021-10-08	14.1	16.88	12.90	Ping
8	2021-10-09	14.7	17.40	13.30	Abe

Next steps: Generate code with dirtydf New interactive sheet

Let's next drop the row from the day that Dr Lowe was sick and didn't take any readings

```
dirtydf.drop([4], inplace=True) # drops index 4 (row 4) within same dataframe
```

```
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Measurer
0	2021-10-01	14.21	17.12	11.55	Ping
1	2021-10-02	14.08	NaN	11.04	Kishav
2	2021-10-03	15.23	NaN	12.21	Bob
3	2021-10-04	14.42	17.26	11.75	Abe
5	2021-10-06	13.77	16331894.00	12.22	Bob
6	2021-10-07	14	17.76	13.10	Kishav
7	2021-10-08	14.1	16.88	12.90	Ping
8	2021-10-09	14.7	17.40	13.30	Abe

Next steps: Generate code with dirtydf New interactive sheet

Now, let's fix those NaNs. Pandas dropna() and fillna() are very flexible. We can force the NA to a value (eg 0) or the min/max/mean/etc of that column. We can also replace it with the last valid entry. Let's try that:

```
dirtydf['Gage 2'].fillna( method ='ffill', inplace = True) # use forward fill method
dirtydf
```

```
/tmp/ipython-input-314749832.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained as
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[co


  dirtydf['Gage 2'].fillna( method ='ffill', inplace = True) # use forward fill method
/tmp/ipython-input-314749832.py:1: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a future version. Use
  dirtydf['Gage 2'].fillna( method ='ffill', inplace = True) # use forward fill method
```

	Date	Gage 1	Gage 2	Gage 3	Measurer
0	2021-10-01	14.21	17.12	11.55	Ping
1	2021-10-02	14.08	17.12	11.04	Kishav
2	2021-10-03	15.23	17.12	12.21	Bob
3	2021-10-04	14.42	17.26	11.75	Abe
5	2021-10-06	13.77	16331894.00	12.22	Bob
6	2021-10-07	14	17.76	13.10	Kishav
7	2021-10-08	14.1	16.88	12.90	Ping
8	2021-10-09	14.7	17.40	13.30	Abe

Next steps: Generate code with dirtydf New interactive sheet

Lets look at info() again

```
dirtydf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8 entries, 0 to 8
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Date      8 non-null      datetime64[ns]
 1   Gage 1    8 non-null      object
 2   Gage 2    8 non-null      float64
 3   Gage 3    8 non-null      float64
 4   Measurer  8 non-null      object
dtypes: datetime64[ns](1), float64(2), object(2)
memory usage: 384.0+ bytes
```

We want all our fields to be numeric so that we can generate statistics. Fix the Dtype of Gage 1:

```
dirtydf['Gage 1'] = pd.to_numeric(dirtydf['Gage 1'])
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Measurer
0	2021-10-01	14.21	17.12	11.55	Ping
1	2021-10-02	14.08	17.12	11.04	Kishav
2	2021-10-03	15.23	17.12	12.21	Bob
3	2021-10-04	14.42	17.26	11.75	Abe
5	2021-10-06	13.77	16331894.00	12.22	Bob
6	2021-10-07	14.00	17.76	13.10	Kishav
7	2021-10-08	14.10	16.88	12.90	Ping
8	2021-10-09	14.70	17.40	13.30	Abe

Next steps: Generate code with dirtydf New interactive sheet

For reasons that will become clearer when we do ML classification, we want to have the Measurer be categorical Dtype rather than Object. We can accomplish this with the following:

```
dirtydf["Measurer"] = dirtydf["Measurer"].astype("category")
```

Let's take another look at the dataframe

```
dirtydf.info()
dirtydf
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8 entries, 0 to 8
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Date      8 non-null      datetime64[ns]
 1   Gage 1    8 non-null      float64
 2   Gage 2    8 non-null      float64
 3   Gage 3    8 non-null      float64
 4   Measurer  8 non-null      category
dtypes: category(1), datetime64[ns](1), float64(3)
memory usage: 532.0 bytes
```

	Date	Gage 1	Gage 2	Gage 3	Measurer
0	2021-10-01	14.21	17.12	11.55	Ping
1	2021-10-02	14.08	17.12	11.04	Kishav
2	2021-10-03	15.23	17.12	12.21	Bob
3	2021-10-04	14.42	17.26	11.75	Abe
5	2021-10-06	13.77	16331894.00	12.22	Bob
6	2021-10-07	14.00	17.76	13.10	Kishav
7	2021-10-08	14.10	16.88	12.90	Ping
8	2021-10-09	14.70	17.40	13.30	Abe

Next steps: Generate code with dirtydf New interactive sheet

Later, we may turn the categorical feature into a numeric value.

Now, what are we going to do about the obviously erroneous reading of Gage 2 on Oct 6?

It is very obvious this is a outlier due to some error.Now let's look at that entry for Gage 2 which seems to be an error.

We will generally just use visualization techniques for this class to help us recognize outliers. This example will be very obvious, but let's go through a set of techniques that can help with datasets with many more observations and with outliers which are not so obvious.

First, look at a sort of the data values for the Gage 2 feature:

```
dirtydf['Gage 2'].sort_values()
```

	Gage 2
7	16.88
0	17.12
2	17.12
1	17.12
3	17.26
8	17.40
6	17.76
5	16331894.00

dtype: float64

Note if there were hundreds or thousands of observations, we'd need to look at head() or tail(). Practice here by inserting a cell to print the first 3 and the last 3 entries of the sorted data

```
print(f"First 3:\n{dirtydf.head(3)}\n")
```

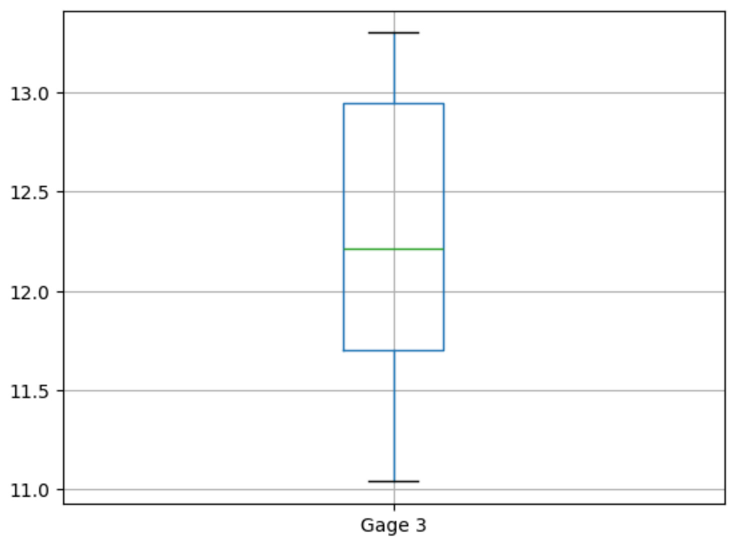
```
print(f"Last 3:\n{dirtydf.tail(3)}")
```

```
First 3:
        Date  Gage 1  Gage 2  Gage 3 Measurer
0 2021-10-01   14.21   17.12   11.55     Ping
1 2021-10-02   14.08   17.12   11.04   Kishav
2 2021-10-03   15.23   17.12   12.21      Bob

Last 3:
        Date  Gage 1  Gage 2  Gage 3 Measurer
6 2021-10-07    14.0   17.76    13.1   Kishav
7 2021-10-08    14.1   16.88    12.9     Ping
8 2021-10-09    14.7   17.40    13.3      Abe
```

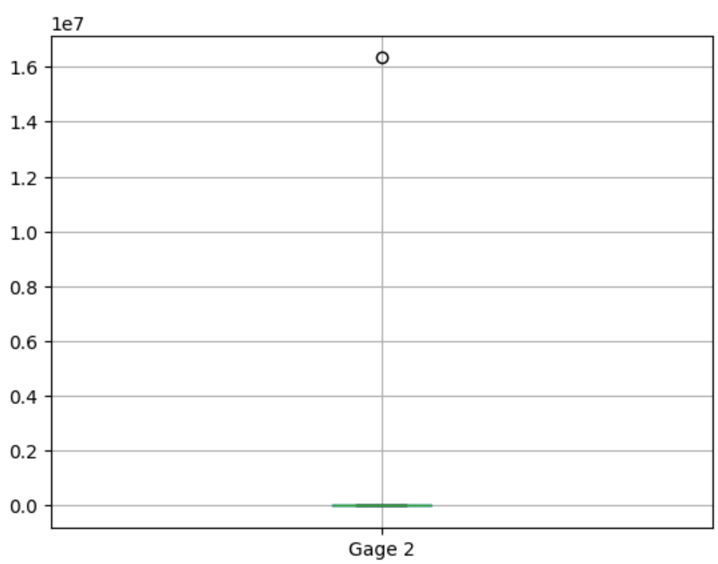
Sorted features make it easier to see what may be abnormally small or large. Another visualization technique is boxplot. Boxplots show the distribution of the data for a row or column with a box for the data from the 1st to the 3rd quartile and "wiskers" for data 1.5X the extent of the box. For many features, data values outside the wiskers can be considered outliers. Be careful, however, with features where the data is exponential in scale. But our values are not exponential, so let's use box plot "wiskers" to guide us. Let's start by generating a boxplot for Gage 3, which seems to have no outliers:

```
boxplot = dirtydf.boxplot(column=['Gage 3'])
```



Now repeat this for Gage 2: Insert a cell to create a boxplot for Gage 2

```
boxplot = dirtydf.boxplot(column=['Gage 2'])
```



Now this value is obviously an error. The outlier is way outside the box and wiskers, which are compressed into a single green line in this plot.

We can (1) try to fix the error if we can determine what a likely correct value is, (2) drop the feature or the observation using dirtydf.drop(), or (3) we can replace outliers with another value 0, min, max, mean, ...

By examination it seems like two measurements, each without their decimal point were incorrectly entered for this datum. Let's assume that the first four digits with the decimal point after the first digit is the correct reading for Gage 2 on Oct 6.

We could try to fix that by doing a replacement: dirtydf.at[index, column] = dirtydf.at[index, column] / 1000000, with the correct index and column label

However, that leaves the erroneous 4 digits at the end of the number. An alternative would be to first do modular division on the incorrect datum to clear the last 4 digits followed by a real division to adjust the decimal point.

Insert cells to correct the datum at index 5 of feature Gage 2 as described.

```
#remove last 4 digits
extraneous_digits = dirtydf['Gage 2'][5] % 10000
dirtydf.loc['Gage 2', 5] = dirtydf['Gage 2'][5] - extraneous_digits

#divide down to correct value
dirtydf.loc['Gage 2', 5] = dirtydf['Gage 2'][5] / 1000000
```

Show your fixed dataframe:

```
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	Measurer	5
0	2021-10-01	14.21	17.12	11.55	Ping	NaN
1	2021-10-02	14.08	17.12	11.04	Kishav	NaN
2	2021-10-03	15.23	17.12	12.21	Bob	NaN
3	2021-10-04	14.42	17.26	11.75	Abe	NaN
5	2021-10-06	13.77	16331894.00	12.22	Bob	NaN
6	2021-10-07	14.00	17.76	13.10	Kishav	NaN
7	2021-10-08	14.10	16.88	12.90	Ping	NaN
8	2021-10-09	14.70	17.40	13.30	Abe	NaN
Gage 2	NaT	NaN	NaN	NaN	NaN	16.331894

Next steps: Generate code with dirtydf New interactive sheet

OK, so now that it is clean let's do some data frame manpulations: Let's add an additional column (attribute + data = feature) that is the average of the readings of Gage 1 and Gage 2. We will use a new series to compute the average then we will insert thate as a new column in the dataframe:

```
avgG1G2=dirtydf[["Gage 1", "Gage 2"]].mean(axis=1)
```

```
avgG1G2
```

	0
0	15.665
1	15.600
2	16.175
3	15.840
5	8165953.885
6	15.880
7	15.490
8	16.050
Gage 2	NaN

dtype: float64

We can use several techniques to insert this numpy series back into our dataframe df.insert(position, name, series to insert) works well for this. df.assign() will also work. Open a cell and use Pandas dataframe .insert() to add avgG1G2 into the dataframe dirtydf at position 4.

```
dirtydf.insert(4, 'avgG1G2', avgG1G2)
```

now show the dataframe to verify that the new feature has been added to the dataframe.

```
dirtydf
```

	Date	Gage 1	Gage 2	Gage 3	avgG1G2	Measurer	5
0	2021-10-01	14.21	17.12	11.55	15.665	Ping	NaN
1	2021-10-02	14.08	17.12	11.04	15.600	Kishav	NaN
2	2021-10-03	15.23	17.12	12.21	16.175	Bob	NaN
3	2021-10-04	14.42	17.26	11.75	15.840	Abe	NaN
5	2021-10-06	13.77	16331894.00	12.22	8165953.885	Bob	NaN
6	2021-10-07	14.00	17.76	13.10	15.880	Kishav	NaN
7	2021-10-08	14.10	16.88	12.90	15.490	Ping	NaN
8	2021-10-09	14.70	17.40	13.30	16.050	Abe	NaN
Gage 2	NaT	NaN	NaN	NaN	NaN	NaN	16.331894

Next steps: Generate code with dirtydf New interactive sheet

Let's look at subsets of our dataset. Let's just look at the data Measured by Abe:

```
dirtydf['Measurer']=='Abe'# which indices correspond to Abe's measurements
```

	Measurer
0	False
1	False
2	False
3	True
5	False
6	False
7	False
8	True
Gage 2	False

dtype: bool

```
dirtydf[dirtydf['Measurer']=='Abe']# subset of dataset from Abe's measurements
```

	Date	Gage 1	Gage 2	Gage 3	avgG1G2	Measurer	5
3	2021-10-04	14.42	17.26	11.75	15.84	Abe	NaN
8	2021-10-09	14.70	17.40	13.30	16.05	Abe	NaN

```
dirtydf.loc[dirtydf['Measurer']=='Abe',['Gage 3']]# the readings from Gage 3 that were measured by Abe
```

	Gage 3
3	11.75
8	13.30

Being able to subset our observations by a value (or range of values) in one feature is important. Equally important is being able to subset the corresponding data from another feature for the subset determined by another feature.

Remember back to our eliminating the observation that had missing data since Dr. Lowe was out sick. In that case we used index 4 to eliminate that observation with df.drop(). If Dr. Lowe turned out to consistently be a bad Gage reader, we could use the above subsetting technique to select only observations made by other observers.

OK, so now back to our weather data in the dataframe df:

```
df.count()
```

	0
Day	30
high degree F	30
low degree F	30
Precip inch	30
Snow inch	30
snow depth inch	30

dtype: int64

Count includes numeric values (not a number entries or NANs are not counted)

Compute the Proportion of observations with precipitation.

```
((df['Precip inch'] != 0).sum()/df['Precip inch'].count())
```

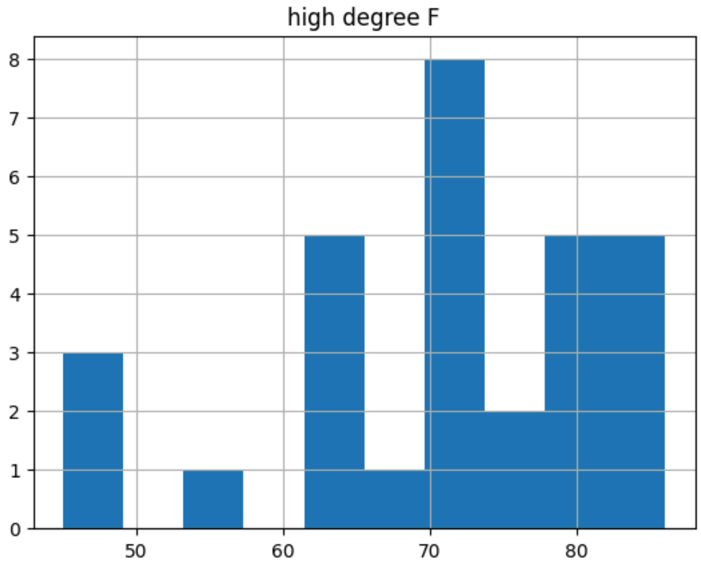
```
np.float64(0.4666666666666667)
```

We could do other, more complex, Proportion calculations. Proportion of days with more than a Trace of rain. For Percent, add a multiplication by 100.

Histograms are a good way to look at Frequency Distribution.
First, use Matplotlib to create a simple histogram

```
df.hist(column='high degree F')
```

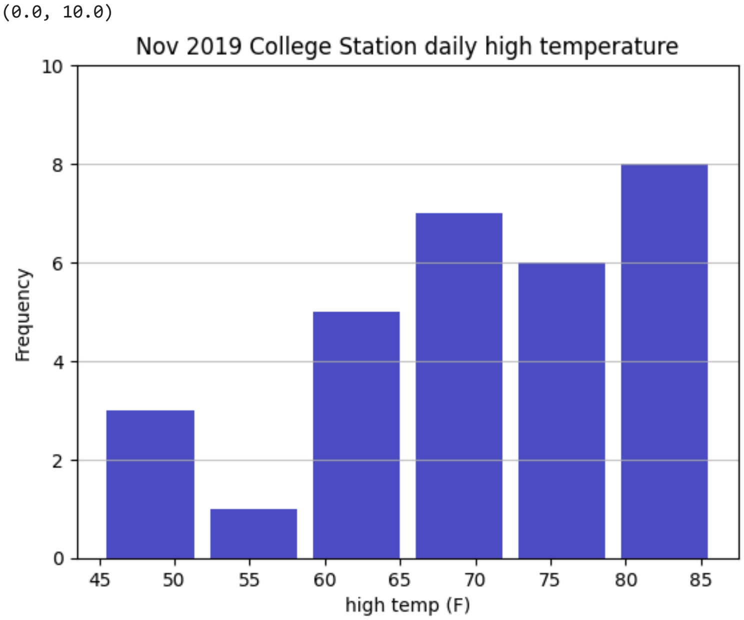
```
array([[<Axes: title={'center': 'high degree F'}>]], dtype=object)
```



Adding axis labels, title, gridlines, limits, etc using Matplotlib a better looking histogram results

```
# An "interface" to matplotlib.axes.Axes.hist() method
n, bins, patches = pyplot.hist(x=df['high degree F'], bins='auto', color='#0504aa',
                            alpha=0.7, rwidth=0.85)
pyplot.grid(axis='y', alpha=0.75)
pyplot.xlabel('high temp (F)')
pyplot.ylabel('Frequency')
pyplot.title('Nov 2019 College Station daily high temperature')
maxfreq = n.max()
# Set a clean upper y-axis limit.
pyplot.ylim(ymax=np.ceil(maxfreq / 10) * 10 if maxfreq % 10 else maxfreq + 10)
```

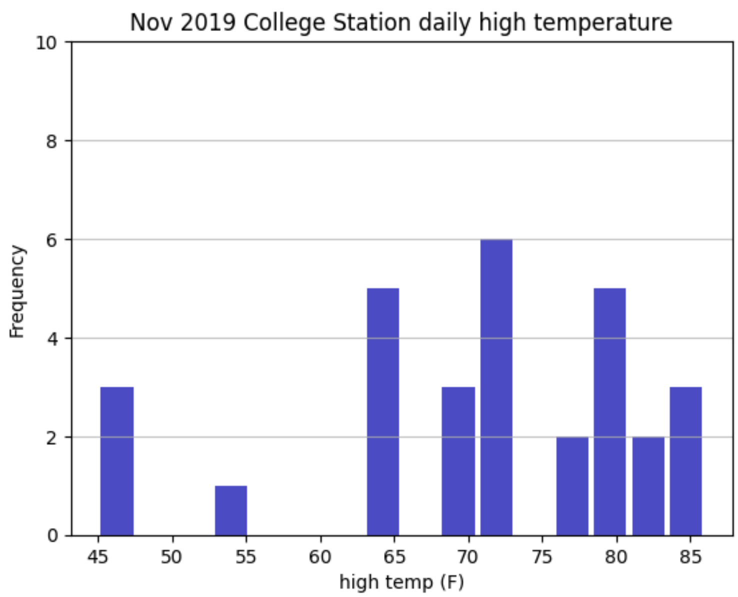
```
(0.0, 10.0)
```



If we want more bins for the histogram adjust the number of bins (6 to 16 is considered best practice). Insert the code after this cell to creat a 16 bin histogram of the daily high temperature:

```
n, bins, patches = pyplot.hist(x=df['high degree F'], bins=16, color='#0504aa',
                            alpha=0.7, rwidth=0.85)
pyplot.grid(axis='y', alpha=0.75)
pyplot.xlabel('high temp (F)')
pyplot.ylabel('Frequency')
pyplot.title('Nov 2019 College Station daily high temperature')
maxfreq = n.max()
# Set a clean upper y-axis limit.
pyplot.ylim(ymax=np.ceil(maxfreq / 10) * 10 if maxfreq % 10 else maxfreq + 10)
```

```
(0.0, 10.0)
```



Measures of Central Tendancy

Mean, median, mode can all be computed on the dataframe columns. Pandas has a method for mean(), median(), and mode() for datframes. Let's find the means of the daily high temperature:

```
print("mean:", df['high degree F'].mean())
```

```
mean: 70.77
```

OR we could find the mean of all features:

```
df.mean()
```

	0
Day	2019-11-15 12:00:00
high degree F	70.77
low degree F	46.933333
Precip inch	0.043
Snow inch	0.0
snow depth inch	0.0

dtype: object

Insert cells to find the median of the high temperature and the mode of the high temperature.

```
print(f"median: {df['high degree F'].median()}")
print(f"mode: {df['high degree F'].mode()}")
```

```
median: 71.55
mode: 0    71.1
1    80.1
Name: high degree F, dtype: float64
```

Now insert a cell to show the medians of all the features in df

```
df.median()
```

	0
Day	2019-11-15 12:00:00
high degree F	71.55
low degree F	45.5
Precip inch	0.0
Snow inch	0.0
snow depth inch	0.0

dtype: object

For Geometric means use the stat library in scipy (note: geometric mean is not suited for mean temperature)

```
from scipy.stats.mstats import gmean
gmean(df['high degree F'])
```

```
np.float64(69.74812411914887)
```

Likewise harmonic mean (also not relevant)

```
from scipy.stats.mstats import hmean
hmean(df['high degree F'])
```

```
np.float64(68.58880347621499)
```

Moving on to Measures of Dispersion or Variation

First, for range we can use numpy "peak to peak" function ptp() to compute ranges. Alternatively, we could in Pandas use df.max() and df.min() and a little math would give the same result,

```
np.ptp(df['high degree F'])
```

```
np.float64(41.0)
```

Next use df.var() to compute variance. You adjust variance for population vs sample by using the ddof (delta degrees of freedom) parameter.

```
# sample variance
df['high degree F'].var()
```

```
131.80493103448276
```

```
#population variance
df['high degree F'].var(ddof=0)
```

```
127.41143333333335
```

For standard deviation, the code is similar

```
# sample standard deviation
df['high degree F'].std()
```

```
11.480632867332826
```

```
#popuation standard variation
df['high degree F'].std(ddof=0)
```

```
11.287667311421494
```

Ranking. Percent rank uses df.rank(). First lets see the high temperatures for the month

```
df['high degree F']
```

	high degree F
0	63.0
1	71.1
2	73.0
3	80.1
4	84.9
5	84.9
6	70.0
7	54.0
8	69.1
9	77.0
10	75.9
11	46.0
12	45.0
13	46.0
14	64.0
15	64.0
16	70.0
17	73.0
18	80.1
19	82.9
20	80.1
21	71.1
22	64.9
23	72.0
24	82.9
25	79.0
26	71.1
27	63.0
28	79.0
29	86.0

dtype: float64

Now for each of those readings, rank shows the percentile rank of that value.

```
df['high degree F'].rank(pct=True)
```

	high degree F
0	0.183333
1	0.466667
2	0.583333
3	0.800000
4	0.950000
5	0.950000
6	0.383333
7	0.133333
8	0.333333
9	0.666667
10	0.633333
11	0.083333
12	0.033333
13	0.083333
14	0.250000
15	0.250000
16	0.383333
17	0.583333
18	0.800000
19	0.883333
20	0.800000
21	0.466667
22	0.300000
23	0.533333
24	0.883333
25	0.716667
26	0.466667
27	0.183333
28	0.716667
29	1.000000

dtype: float64

Now quantile rank to get data quartiles.

```
pd.qcut(df['low degree F'], q=4)
```

	low degree F
0	(27.999, 39.225]
1	(27.999, 39.225]
2	(39.225, 45.5]
3	(45.5, 53.775]
4	(53.775, 70.0]
5	(53.775, 70.0]
6	(45.5, 53.775]
7	(39.225, 45.5]
8	(39.225, 45.5]
9	(39.225, 45.5]
10	(27.999, 39.225]
11	(27.999, 39.225]
12	(27.999, 39.225]
13	(27.999, 39.225]
14	(27.999, 39.225]
15	(27.999, 39.225]
16	(39.225, 45.5]
17	(45.5, 53.775]
18	(45.5, 53.775]
19	(53.775, 70.0]
20	(53.775, 70.0]
21	(45.5, 53.775]
22	(39.225, 45.5]
23	(39.225, 45.5]
24	(45.5, 53.775]
25	(53.775, 70.0]
26	(53.775, 70.0]
27	(45.5, 53.775]
28	(53.775, 70.0]
29	(53.775, 70.0]

dtype: category

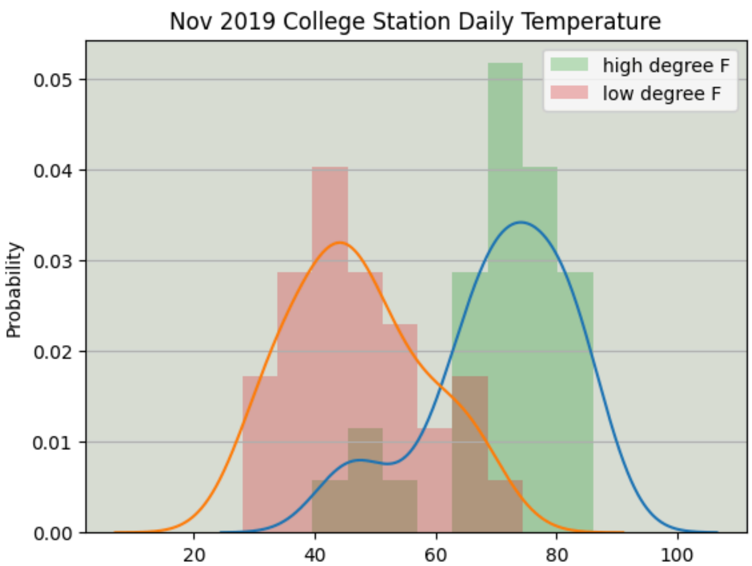
Finally, a summary of the characteristics of the dataframe which includes many of the statistics can be displayed by using describe()

```
df.describe()
```

	Day	high degree F	low degree F	Precip inch	Snow inch	snow depth inch
count	30	30.000000	30.000000	30.000000	30.0	30.0
mean	2019-11-15 12:00:00	70.770000	46.933333	0.043000	0.0	0.0
min	2019-11-01 00:00:00	45.000000	28.000000	0.000000	0.0	0.0
25%	2019-11-08 06:00:00	64.225000	39.225000	0.000000	0.0	0.0
50%	2019-11-15 12:00:00	71.550000	45.500000	0.000000	0.0	0.0
75%	2019-11-22 18:00:00	79.825000	53.775000	0.017500	0.0	0.0
max	2019-11-30 00:00:00	86.000000	70.000000	0.620000	0.0	0.0
std	NaN	11.480633	11.223784	0.118457	0.0	0.0

More sophisticated distribution analysis and ploting can be done with the Dataframe data and Matplotlib. For example to compare high and low temperature distributionshistograms (and Gaussian Kernel Density Estimates as distribution model) we can use this plot:

```
fig, ax = pyplot.subplots()
df[["high degree F", "low degree F"]].plot.kde(ax=ax, legend=False, title='Nov 2019 College Station Daily Temperature')
df[["high degree F", "low degree F"]].plot.hist(density=True, ax=ax, alpha=0.3)
ax.set_ylabel('Probability')
ax.grid(axis='y')
ax.set_facecolor('#d8dcd6')
```



PART 2: Loading and Cleaning Leaf Blower Data

```
# change the directory as needed
!ls drive/MyDrive/ECEN250_Lab2_LeafBlowers.csv
```

```
drive/MyDrive/ECEN250_Lab2_LeafBlowers.csv
```

```
# importing dataset
df = pd.read_csv('drive/MyDrive/ECEN250_Lab2_LeafBlowers.csv')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112 entries, 0 to 111
Data columns (total 16 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   manuf         100 non-null    object
 1   model         100 non-null    object
 2   retail        100 non-null    object
 3   volt          100 non-null    float64
 4   no batteries  100 non-null    float64
 5   bat Ahr       100 non-null    float64
 6   bat lb        100 non-null    float64
 7   motor type    100 non-null    object
 8   sound rating  98 non-null     float64
 9   hi cfm        100 non-null    float64
 10  lo cfm        100 non-null    float64
 11  hi mph        100 non-null    float64
 12  lo mph        99 non-null     float64
 13  weight        100 non-null    float64
 14  price         100 non-null    float64
 15  source        100 non-null    object
dtypes: float64(11), object(5)
```

```
memory usage: 14.1+ KB
```

Let's look at what we read in to make sure it's what we expected:

```
df.head(10)
```

	manuf	model	retail	volt	no batteries	bat Ahr	bat lb	motor type	sound rating	hi cfm	lo cfm	hi mph	lo mph	weight	price
0	Black+Decker	LSW221	Tractor Supply Co	20.0	1.0	1.5	0.90	brushed	61.0	100.0	100.0	130.0	130.0	3.70	99.99
1	Black+Decker	LSW321	Tractor Supply Co	20.0	1.0	2.0	0.90	brushed	54.0	100.0	100.0	130.0	130.0	3.70	119.99
2	Black+Decker	LSW321	Walmart	20.0	1.0	2.0	0.90	brushed	54.0	100.0	100.0	130.0	130.0	3.70	128.00
3	Black+Decker	LSW40C	Home Depot	40.0	1.0	1.5	1.90	unspecified	59.0	90.0	90.0	125.0	125.0	6.00	129.00
4	Black+Decker	LSWV36	Home Depot	40.0	1.0	1.5	1.90	unspecified	65.0	90.0	90.0	120.0	120.0	6.90	168.00
5	Craftsman	CMCBL710M1	Lowes	20.0	1.0	4.0	0.77	brushed	92.0	200.0	200.0	90.0	90.0	5.05	89.98
6	Craftsman	CMCBL730P1	Lowes	20.0	1.0	5.0	2.60	brushless	63.0	410.0	410.0	110.0	110.0	6.50	129.00
7	Dewalt	DCBL722BDCB246K	Home Depot	20.0	2.0	6.0	1.80	brushless	61.0	450.0	450.0	125.0	125.0	6.30	348.00
8	Dewalt	DCBL722P1	Home Depot	20.0	1.0	5.0	1.40	brushless	62.0	450.0	450.0	125.0	125.0	6.70	199.00
9	Dewalt	DCBL770X1	Home Depot	60.0	1.0	3.0	2.70	brushless	67.0	423.0	423.0	129.0	129.0	10.10	319.00

Next steps: Generate code with df New interactive sheet

Manufacturer, model, retail, and source are going to be non-numeric by nature. These are currently objects, because some entries may be numeric and some string. We will leave them as they are since they will not be used in our statistics or ML data analysis. The feature motor type contains strings: brushed, brushless, or unspecified. It is currently an object datatype. This feature -- is categorical. Is it nominal or ordinal?? We will use it a lot in our analysis so let's turn it into a numerical that we can manipulate. We can do that with the following python cell (notice when we use flag inplace=True we are directly modifying our df -- if not done inplace replace() returns a new modified df):

```
df['motor type'].replace(['brushless', 'unspecified', 'brushed'],
                        [0, 0.5, 1], inplace=True)
```

```
/tmp/ipython-input-885561029.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained as
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[co


  df['motor type'].replace(['brushless', 'unspecified', 'brushed'],
/tmp/ipython-input-885561029.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future v
  df['motor type'].replace(['brushless', 'unspecified', 'brushed'],
```

Let's verify this worked by doing df.head(10) again

```
df.head(10)
```

	manuf	model	retail	volt	no batteries	bat Ahr	bat lb	motor type	sound rating	hi cfm	lo cfm	hi mph	lo mph	weight	price
0	Black+Decker	LSW221	Tractor Supply Co	20.0	1.0	1.5	0.90	1.0	61.0	100.0	100.0	130.0	130.0	3.70	99.99
			Tractor												