Data Preparation

Austin TX, Weather in Novemebr

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Abstract

In this study we have captured weather information for the city of Austin, TX via three different data sources listed below:

- Kaggle Austin weather analysis dataset in CSV format: link: https://www.kaggle.com/datasets/grubenm/austin-weather
- Austin weather through from OpenWeatherMap API in JSON format: link: https://home.openweathermap.org/history_forecast_bulks/new
- Austin weather from Wunderground for the month of Nov-2022 in HTML format: link: https://www.wunderground.com/history/monthly/us/tx/austin/KAUS/date/2022-11

Goal:

Overall aim of this study is to be able to gether data from different data type sources and perform cleaning/transformation and finally store them in a database and perform post-processing with visualized exports.

Steps Taken:

- 1- Download Kaggle dataset through the mentioned link.
- 2- Parse and then export/transform weather information through a web scraping process of the provided link above.
- 3- Hit the openweathermap API and export weather information a from json formatted data.

Finally having all these clean data we filter the weather info for the month of November and store them all in three different tables of SQLite data based, and provide visualized comparative graghs of them.

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import sqlite3
```

Load already processed datasets

Perform final column name change/transformations

In [ ]:
```
df_api = pd.read_csv('Austin_weather_api.csv')
df_kaggle = pd.read_csv('Austin_weather_kaggle_processed.csv')
df_website = pd.read_csv('Austin_weather_html.csv')

print('df_api: ',df_api.shape)
print('df_kaggle: ',df_kaggle.shape)
print('df_html: ',df_website.shape)
```

```
df_api:  (30, 24)
df_kaggle:  (1183, 21)
df_html:  (30, 17)
```

Kaggle dataset clean ups/ trsansformations

df_kaggle is holding data for years 2013 to July 2017, not Nov 2022. For this reason I will extract data for Nov 2014 Which has less missing data (only one day Nov 3th) compared to other yesrs.

Kaggle:

In [ ]:
```
# Split 'Data' to year, month and day

df_kaggle['year'] = [str(x).split('/')[2] for x in df_kaggle['Date']]
df_kaggle['day'] = [int(str(x).split('/')[1]) for x in df_kaggle['Date']]
df_kaggle['month'] = [str(x).split('/')[0] for x in df_kaggle['Date']]
#-------------------------------------------------------------------------


#df_kaggle_group = df_kaggle.groupby(['year', 'month'])['Date'].count()

df_kaggle = df_kaggle[(df_kaggle['year'] == '2014') & (df_kaggle['month'] == '11')]  # Filter data for Nov 2014
df_kaggle['Date'] = df_kaggle['day']                                                 # All datasets with come in this format
df_kaggle.drop(columns=['year','month','day'], inplace = True)                       # Drops unnecessary columns
#-------------------------------------------------------------------------

# Add an index of 'k_' to the begining of each attributes
# This because we want to distingush attributes for each datasets.
kaggle_columns = list(df_kaggle.columns)
for i in range(len(kaggle_columns)):
```

```
    if (kaggle_columns[i] != 'Date'):
        kaggle_columns[i] = 'k_' + kaggle_columns[i]


kaggle_columns = list(df_kaggle.columns)
for i in range (len(kaggle_columns)):
    kaggle_columns[i] = kaggle_columns[i].lower()

    if (kaggle_columns[i] != 'date'):
        kaggle_columns[i] = 'k_' + kaggle_columns[i]
    kaggle_columns[i] = kaggle_columns[i].replace('date','Date')
    kaggle_columns[i] = kaggle_columns[i].replace('f','')
    kaggle_columns[i] = kaggle_columns[i].replace('high','_max')
    kaggle_columns[i] = kaggle_columns[i].replace('low','_min')
    kaggle_columns[i] = kaggle_columns[i].replace('avg','_avg')
    kaggle_columns[i] = kaggle_columns[i].replace('percent','')
    kaggle_columns[i] = kaggle_columns[i].replace('sealevel','')
    kaggle_columns[i] = kaggle_columns[i].replace('inches','')
    kaggle_columns[i] = kaggle_columns[i].replace('miles','')
    kaggle_columns[i] = kaggle_columns[i].replace('mph','')
    kaggle_columns[i] = kaggle_columns[i].replace('mph','')
    kaggle_columns[i] = kaggle_columns[i].replace('dewpoint','dew_point')

df_kaggle.columns = kaggle_columns
df_kaggle['Date'] = df_kaggle['Date'].astype(int)
df_kaggle.head()
```

Out[ ]:

	Date	k_temp_max	k_temp_avg	k_temp_min	k_dew_point_max	k_dew_point_avg	k_dew_point_min	k_humidity_max	k_humidity_avg	k_humidity_min	...	k_pressure_avg	k_pressure_min	k_visibility_max	k_visibility_avg	k_visibility_min	k_wind_max	k_wind_avg	k_windgust	k_precipitationsum	k_events
281	1	68	58	47	43	39	37	71	54	37	...	30.34	30.28	10	10	10	9	5	14	0.00	
282	2	75	62	48	52	45	39	80	61	41	...	30.26	30.18	10	10	10	15	6	25	0.00	
283	4	75	67	58	69	63	57	100	87	73	...	30.09	30.01	10	8	2	17	5	28	0.56	Rain
284	5	59	57	55	58	56	54	100	97	93	...	30.16	30.08	10	6	2	13	6	20	1.51	Rain
285	6	63	59	55	56	51	46	93	75	56	...	30.28	30.22	10	10	5	10	4	17	0.04	Rain

5 rows × 21 columns

OpenWeathermap called 'api' dataset for simplicity

In [ ]:

```
# Apply some column name changes
# Add 'a_' index to beginning of each attributes, and common column as for other datasets

api_columns = list(df_api.columns)
for i in range (len(api_columns)):

    if (api_columns[i] != 'date'):
        api_columns[i] = 'a_' + api_columns[i]

    api_columns[i] = api_columns[i].lower()
    api_columns[i] = api_columns[i].replace('mean', 'avg')
    api_columns[i] = api_columns[i].replace('main_', '')
    api_columns[i] = api_columns[i].replace('.1', '')
    api_columns[i] = api_columns[i].replace('date', 'Date')

df_api.columns = api_columns
#-----------------------------------------------------------------

# Split 'Data' to year, month and day
df_api['year'] = [str(x).split('-')[0] for x in df_api['Date']]
df_api['day'] = [int(str(x).split('-')[2]) for x in df_api['Date']]
df_api['month'] = [str(x).split('-')[1] for x in df_api['Date']]
df_api['Date'] = df_api['day']                                      # All datasets with come in this format

df_api.drop(columns=['year','month','day'], inplace = True)         # Drops unnecessary columns
#-----------------------------------------------------------------

# Metric conversion pressure to PSI and Visibility to Miles
for index, row in df_api.iterrows():
    pressure = row['a_pressure_min']
    psi = (pressure * 0.0145) *  2.03602
    df_api.loc[index, ['a_pressure_min']] = psi

    pressure = row['a_pressure_avg']
    psi = (pressure * 0.0145) *  2.03602
    df_api.loc[index, ['a_pressure_avg']] = psi

    pressure = row['a_pressure_max']
    psi = (pressure * 0.0145) *  2.03602
    df_api.loc[index, ['a_pressure_max']] = psi


    visibility = row['a_visibility_avg']
    df_api.loc[index, ['a_visibility_avg']] = visibility/1609

df_api.head()
```

Out[ ]:

	Date	a_visibility_avg	a_snow_avg	a_wind_speed_min	a_wind_speed_avg	a_wind_speed_max	a_wind_deg_min	a_wind_deg_avg	a_wind_deg_max	a_temp_min	...	a_feels_like_max	a_pressure_min	a_pressure_avg	a_pressure_max	a_humidity_min	a_humidity_avg	a_humidity_max	a_dew_point_min	a_dew_point_avg	a_dew_point_max
0	1	6.206132	0.0	0.00	4.679167	8.99	0	128.458333	360	55.42	...	70.63	29.935602	30.067222	30.171780	57	81.750000	96	54.59	58.840000	66.65
1	2	5.920447	0.0	0.00	3.819583	7.00	0	95.708333	221	58.28	...	77.86	30.053691	30.147178	30.230825	67	84.958333	94	57.25	60.628750	65.48
2	3	5.837088	0.0	3.44	10.071667	19.57	0	156.250000	190	68.58	...	86.25	29.876557	30.013098	30.083214	60	82.791667	94	64.99	68.006250	70.21
3	4	6.063290	0.0	8.05	15.317500	21.85	144	168.083333	190	71.67	...	91.17	29.610857	29.805212	29.906080	65	83.458333	93	67.62	71.251667	74.48
4	5	6.122773	0.0	0.00	5.559167	12.66	0	171.291667	357	50.02	...	79.52	29.728946	29.853186	29.965124	39	58.125000	92	37.54	48.070833	69.51

5 rows × 24 columns

Website driven data

In [ ]:
```
# Apply some column name changes
# Add 'w_' index to beginning of each attributes, and common column as for other datasets

df_website_columns = list(df_website.columns)

for i in range (len(df_website_columns)):

    if (df_website_columns[i] != 'Time'):
        df_website_columns[i] = 'w_' + df_website_columns[i]

    df_website_columns[i] = df_website_columns[i].lower()
    df_website_columns[i] = df_website_columns[i].replace(' (°f)','')
    df_website_columns[i] = df_website_columns[i].replace(' (%)','')
    df_website_columns[i] = df_website_columns[i].replace(' (mph)','')
    df_website_columns[i] = df_website_columns[i].replace(' (in)','')
    df_website_columns[i] = df_website_columns[i].replace(' ','_')
    df_website_columns[i] = df_website_columns[i].replace('temperature','temp')
    df_website_columns[i] = df_website_columns[i].replace('time','Date')

df_website.columns = df_website_columns
#-----------------------------------------------------------------

# Split 'Data' to year, month and day

df_website['month'] = [str(x).split('/')[1]  for x in df_website['Date']]
df_website['day'] = [int(str(x).split('/')[2])   for x in df_website['Date']]
df_website['Date'] = df_website['day']                                  # All datasets with come in this format
df_website.drop(columns=['month','day'], inplace = True)                # Drops unnecessary columns
df_website.head()
```

Out[ ]:

	Date	w_temp_max	w_temp_avg	w_temp_min	w_dew_point_max	w_dew_point_avg	w_dew_point_min	w_humidity_max	w_humidity_avg	w_humidity_min	w_wind_speed_max	w_wind_speed_avg	w_wind_speed_min	w_pressure_max	w_pressure_avg	w_pressure_min	w_precipitation
0	2022	66	60.8	55	62	59.5	55	100	95.7	75	7	2.4	0	29.6	29.6	29.5	0.05
1	2022	76	63.6	54	68	60.4	54	100	90.3	64	8	3.6	0	29.7	29.6	29.5	0.01
2	2022	84	74.6	69	70	68.7	65	100	83.2	53	20	12.2	7	29.5	29.4	29.3	0.00
3	2022	85	73.5	59	75	69.0	52	97	86.5	63	22	12.8	3	29.4	29.3	29.1	0.00
4	2022	71	59.4	50	55	49.5	42	100	73.0	42	12	5.2	0	29.4	29.3	29.3	0.41

CREATING DATABASE

In [ ]:
```
with sqlite3.connect('austin_weather.db') as conn:
    cursor = conn.cursor()
    cursor.execute("""CREATE TABLE IF NOT EXISTS api (Date int, a_visibility_avg float, a_snow_avg float,
                                            a_wind_speed_min float, a_wind_speed_avg float, a_wind_speed_max float,
                                            a_wind_deg_min float, wind_deg_avg float, wind_deg_max float,
                                            a_temp_min float, a_temp_avg float, a_temp_max float,
                                            a_feels_like_min float, a_feels_like_avg float, a_feels_like_max float,
                                            a_pressure_min float, a_pressure_avg float, a_pressure_max float,
                                            a_humidity_min float, a_humidity_avg float, a_humidity_max float,
                                            a_dew_point_min float, a_dew_point_avg float, a_dew_point_max float,
                                            PRIMARY KEY (Date))""")

    cursor.execute("""CREATE TABLE IF NOT EXISTS kaggle (Date int, k_temp_max float, k_temp_avg float, k_temp_min float,
                                            k_dew_point_max float, k_dew_point_avg float, k_dew_point_min float,
                                            k_humidity_max float, k_humidity_avg float, k_humidity_min float,
                                            k_pressure_max float, k_pressure_avg float, k_pressure_min float,
                                            k_visibility_max float, k_visibility_avg float, k_visibility_min float,
                                            k_wind_max float, k_wind_avg float, k_windgust float, k_precipitationsum float,
                                            k_events text,
                                            PRIMARY KEY (Date))""")

    cursor.execute("""CREATE TABLE IF NOT EXISTS website (Date int,
                                        w_temp_max float, w_temp_avg float, w_temp_min float,
                                        w_dew_point_max float, w_dew_point_avg float, w_dew_point_min float,
                                        w_humidity_max float, w_humidity_avg float, w_humidity_min float,
                                        w_wind_speed_max float, w_wind_speed_avg float, w_wind_speed_min float,
                                        w_pressure_max float, w_pressure_avg float, w_pressure_min float,
                                        w_precipitation float,
                                        PRIMARY KEY (Date))""")

    #-------------------------------------------------------------------------------
```

```
    # Import datasets into the created database tables

    df_api.to_sql('api',conn,if_exists='replace',index=False)
    df_kaggle.to_sql('kaggle',conn,if_exists='replace',index=False)
    df_website.to_sql('website',conn,if_exists='replace',index=False)

    conn.commit()
```

Read data from DataBase

In [ ]:
```
with sqlite3.connect('austin_weather.db') as conn:
    cursor = conn.cursor()

    # Perform LEFT JOIN on all datasets based on the common key 'Date'
    df_combined = pd.read_sql_query("""SELECT *
                                    FROM
                                    (SELECT api.*, website.* FROM api LEFT JOIN website
                                    ON api.Date = website.Date) t1 LEFT JOIN kaggle as t2
                                    ON t1.Date = t2.Date""", conn)

df_combined.head()
```

Out[ ]:

	Date	a_visibility_avg	a_snow_avg	a_wind_speed_min	a_wind_speed_avg	a_wind_speed_max	a_wind_deg_min	a_wind_deg_avg	a_wind_deg_max	a_temp_min	...	k_pressure_avg	k_pressure_min	k_visibility_max	k_visibility_avg	k_visibility_min	k_wind_max	k_wind_avg	k_windgust	k_precipitationsum	k_events
0	1	6.206132	0.0	0.00	4.679167	8.99	0	128.458333	360	55.42	...	30.34	30.28	10.0	10.0	10.0	9.0	5.0	14.0	0.00	
1	2	5.920447	0.0	0.00	3.819583	7.00	0	95.708333	221	58.28	...	30.26	30.18	10.0	10.0	10.0	15.0	6.0	25.0	0.00	
2	3	5.837088	0.0	3.44	10.071667	19.57	0	156.250000	190	68.58	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	None
3	4	6.063290	0.0	8.05	15.317500	21.85	144	168.083333	190	71.67	...	30.09	30.01	10.0	8.0	2.0	17.0	5.0	28.0	0.56	Rain
4	5	6.122773	0.0	0.00	5.559167	12.66	0	171.291667	357	50.02	...	30.16	30.08	10.0	6.0	2.0	13.0	6.0	20.0	1.51	Rain

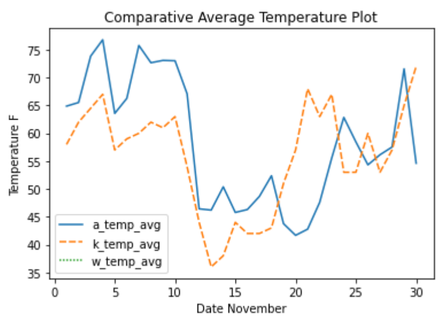
5 rows × 62 columns

Visualizations

Comparative line graphs for the merged dataset having data from all three datasets

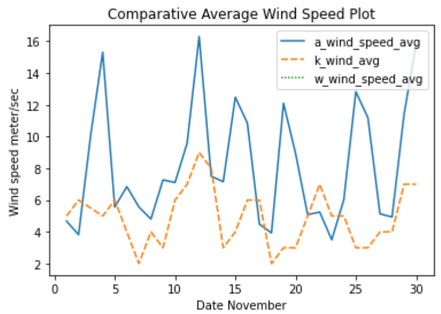
In [ ]:
```
# Plot the average tempreture all datasets against each other
# w_temp_avg,  a_temp_avg, k_temp_avg
# 'w' stands for data pulled from website
# 'a' stands for data pulled via api
# 'k' stands for data pulled from kaggle dataset


df_temp = df_combined[['Date','w_temp_avg', 'a_temp_avg', 'k_temp_avg']]
df_temp = df_temp.T.groupby(level=0).first().T
df_temp.set_index('Date', inplace= True)

ax = sns.lineplot(data=df_temp)
ax.set(xlabel='Date November', ylabel='Temperature F', title='Comparative Average Temperature Plot')
ax.legend(loc='lower left')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x198a49f71c0>
```



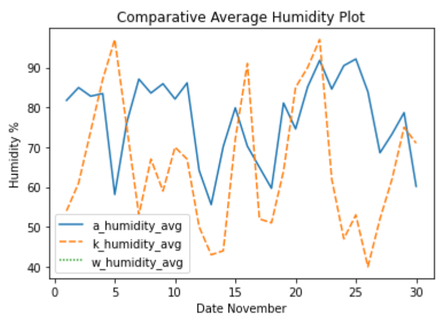
In [ ]:
```
df_wind = df_combined[['Date','w_wind_speed_avg', 'a_wind_speed_avg', 'k_wind_avg']]
df_wind = df_wind.T.groupby(level=0).first().T
df_wind.set_index('Date', inplace= True)
ax = sns.lineplot(data=df_wind)
ax.set(xlabel='Date November', ylabel='Wind speed meter/sec', title='Comparative Average Wind Speed Plot')
ax.legend(loc='upper right')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x198a4b14c40>
```



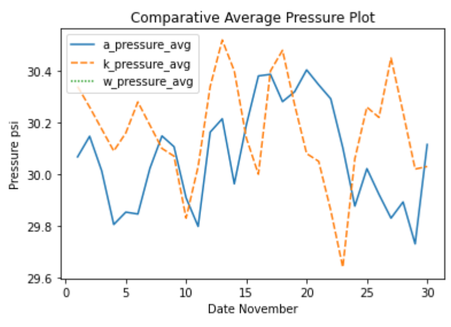
In [ ]:
```
df_humidity = df_combined[['Date','w_humidity_avg', 'a_humidity_avg', 'k_humidity_avg']]
df_humidity = df_humidity.T.groupby(level=0).first().T
df_humidity.set_index('Date', inplace= True)
ax = sns.lineplot(data=df_humidity)
ax.set(xlabel='Date November', ylabel='Humidity %', title='Comparative Average Humidity Plot')
ax.legend(loc='lower left')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x198a4b722b0>
```



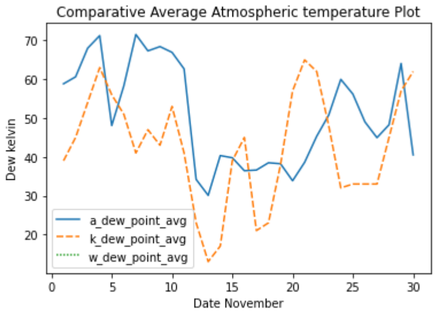
In [ ]:
```
df_psi = df_combined[['Date','w_pressure_avg', 'a_pressure_avg', 'k_pressure_avg']]
df_psi = df_psi.T.groupby(level=0).first().T
df_psi.set_index('Date', inplace= True)

ax = sns.lineplot(data=df_psi)
ax.set(xlabel='Date November', ylabel='Pressure psi', title='Comparative Average Pressure Plot')
ax.legend(loc='upper left')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x198a4c587f0>
```



In [ ]:
```
df_dew = df_combined[['Date','w_dew_point_avg', 'a_dew_point_avg', 'k_dew_point_avg']]
df_dew = df_dew.T.groupby(level=0).first().T
df_dew.set_index('Date', inplace= True)

ax = sns.lineplot(data=df_dew)

ax.set(xlabel='Date November', ylabel='Dew kelvin', title='Comparative Average Atmospheric temperature Plot')
ax.legend(loc='lower left')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x198a4ce9430>
```

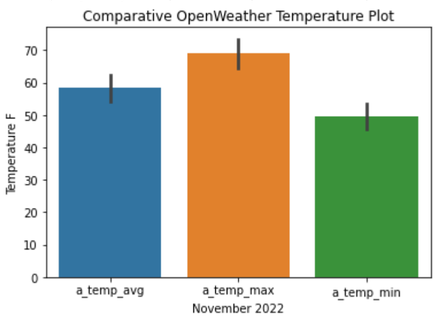


Comparative bar graphs for each data set

In [ ]:
```
with sqlite3.connect('austin_weather.db') as conn:
    cursor = conn.cursor()

    # Perform LEFT JOIN on all datasets based on the common key 'Date'
    df_api_db = pd.read_sql_query("""SELECT * FROM api""", conn)
    df_website_db = pd.read_sql_query("""SELECT * FROM website""", conn)
    df_kaggle_db = pd.read_sql_query("""SELECT * FROM kaggle""", conn)
```

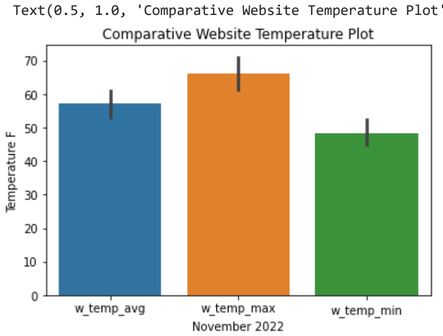
In [ ]:
```
df_temp = df_api_db[['Date','a_temp_min', 'a_temp_avg', 'a_temp_max']]
df_temp = df_temp.T.groupby(level=0).first().T
df_temp.set_index('Date', inplace= True)

ax = sns.barplot(data=df_temp)
ax.set(xlabel='November 2022', ylabel='Temperature F', title='Comparative OpenWeather Temperature Plot')
```

Out[ ]:
```
[Text(0.5, 0, 'November 2022'),
 Text(0, 0.5, 'Temperature F'),
 Text(0.5, 1.0, 'Comparative OpenWeather Temperature Plot')]
```



In [ ]:
```
df_temp = df_website_db[['Date','w_temp_min', 'w_temp_avg', 'w_temp_max']]
df_temp = df_temp.T.groupby(level=0).first().T
df_temp.set_index('Date', inplace= True)

ax = sns.barplot(data=df_temp)
ax.set(xlabel='November 2022', ylabel='Temperature F', title='Comparative Website Temperature Plot')
```

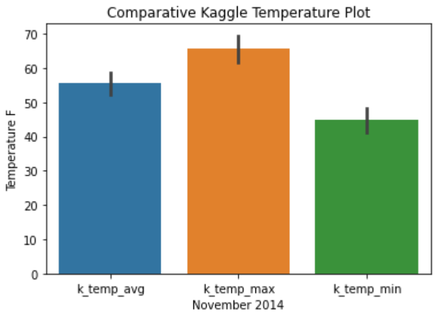
Out[ ]:
```
[Text(0.5, 0, 'November 2022'),
 Text(0, 0.5, 'Temperature F'),
 Text(0.5, 1.0, 'Comparative Website Temperature Plot')]
```



In [ ]:
```
df_temp = df_kaggle_db[['Date','k_temp_min', 'k_temp_avg', 'k_temp_max']]
df_temp = df_temp.T.groupby(level=0).first().T
df_temp.set_index('Date', inplace= True)
```

```
ax = sns.barplot(data=df_temp)
ax.set(xlabel='November 2014', ylabel='Temperature F', title='Comparative Kaggle Temperature Plot')
```

Out[ ]:
```
[Text(0.5, 0, 'November 2014'),
 Text(0, 0.5, 'Temperature F'),
 Text(0.5, 1.0, 'Comparative Kaggle Temperature Plot')]
```



Datasets

In [ ]:
```
df_api_db
```

Out[ ]:

	Date	a_visibility_avg	a_snow_avg	a_wind_speed_min	a_wind_speed_avg	a_wind_speed_max	a_wind_deg_min	a_wind_deg_avg	a_wind_deg_max	a_temp_min	...	a_feels_like_max	a_pressure_min	a_pressure_avg	a_pressure_max	a_humidity_min	a_humidity_avg	a_humidity_max	a_dew_point_min	a_dew_point_avg	a_dew_point_max
0	1	6.206132	0.0	0.00	4.679167	8.99	0	128.458333	360	55.42	...	70.63	29.935602	30.067222	30.171780	57	81.750000	96	54.59	58.840000	66.65
1	2	5.920447	0.0	0.00	3.819583	7.00	0	95.708333	221	58.28	...	77.86	30.053691	30.147178	30.230825	67	84.958333	94	57.25	60.628750	65.48
2	3	5.837088	0.0	3.44	10.071667	19.57	0	156.250000	190	68.58	...	86.25	29.876557	30.013098	30.083214	60	82.791667	94	64.99	68.006250	70.21
3	4	6.063290	0.0	8.05	15.317500	21.85	144	168.083333	190	71.67	...	91.17	29.610857	29.805212	29.906080	65	83.458333	93	67.62	71.251667	74.48
4	5	6.122773	0.0	0.00	5.559167	12.66	0	171.291667	357	50.02	...	79.52	29.728946	29.853186	29.965124	39	58.125000	92	37.54	48.070833	69.51
5	6	6.215040	0.0	0.00	6.849583	19.57	0	164.250000	230	48.22	...	87.78	29.787991	29.845805	29.906080	55	76.208333	91	50.05	58.298750	71.51
6	7	6.096048	0.0	0.00	5.571667	11.50	0	119.083333	200	69.03	...	88.02	29.847035	30.022939	30.142258	70	87.083333	96	67.73	71.543750	74.91
7	8	5.956080	0.0	0.00	4.803750	10.00	0	92.916667	180	62.58	...	79.68	30.053691	30.148409	30.230825	71	83.583333	93	61.32	67.317500	70.77
8	9	6.215040	0.0	3.44	7.270417	16.11	0	112.875000	180	66.45	...	84.02	29.994647	30.106585	30.171780	66	85.916667	94	65.68	68.426667	70.25
9	10	6.104982	0.0	3.44	7.111250	12.66	0	123.750000	200	66.22	...	83.17	29.758468	29.908540	29.994647	63	82.083333	93	65.16	66.936250	69.82
10	11	6.215040	0.0	1.99	9.574583	23.02	95	213.916667	350	45.39	...	78.82	29.728946	29.797831	29.935602	68	86.125000	92	44.96	62.670000	68.72
11	12	6.215040	0.0	11.50	16.305833	21.85	10	268.166667	360	38.28	...	54.50	29.965124	30.163170	30.289870	38	64.166667	91	30.22	34.191667	43.83
12	13	3.884400	0.0	4.00	7.507083	10.36	6	58.916667	350	32.02	...	55.80	30.053691	30.214834	30.319392	31	55.583333	77	26.28	30.074583	33.17
13	14	5.637637	0.0	5.01	7.158333	10.36	0	139.833333	360	45.32	...	51.93	29.876557	29.962664	30.053691	38	70.166667	92	30.02	40.332083	50.40
14	15	6.215040	0.0	9.22	12.482500	17.27	10	236.833333	360	37.38	...	50.83	29.906080	30.191462	30.348914	64	79.875000	92	33.87	39.767917	49.39
15	16	6.215040	0.0	7.00	10.850000	18.01	10	34.833333	58	39.58	...	53.35	30.289870	30.380897	30.467003	44	70.250000	85	32.83	36.425833	38.35
16	17	6.215040	0.0	1.01	4.482917	10.36	0	189.583333	350	39.22	...	55.90	30.289870	30.387047	30.467003	42	64.958333	83	32.97	36.602917	39.61
17	18	6.215040	0.0	0.00	3.931667	8.05	0	84.416667	180	47.57	...	53.20	30.201303	30.281259	30.319392	48	59.666667	76	35.13	38.480000	42.13
18	19	6.164466	0.0	1.99	12.100833	19.57	0	86.833333	360	36.28	...	50.20	30.260347	30.319392	30.407959	64	81.083333	91	33.89	38.227083	43.09
19	20	6.215040	0.0	4.61	8.933750	17.27	18	243.083333	360	37.38	...	42.51	30.348914	30.404268	30.467003	53	74.583333	89	30.29	33.837500	36.54
20	21	6.063290	0.0	1.99	5.083333	9.22	10	187.500000	360	39.38	...	43.95	30.319392	30.346454	30.378436	72	85.125000	91	34.84	38.599583	43.07
21	22	4.968070	0.0	1.99	5.249167	8.01	0	94.666667	360	43.29	...	53.94	30.171780	30.292330	30.348914	85	91.791667	95	42.53	45.308750	51.17
22	23	6.146649	0.0	0.00	3.501667	8.01	0	95.708333	330	50.58	...	62.01	29.906080	30.102895	30.201303	67	84.583333	93	49.23	50.788333	53.85
23	24	3.528796	0.0	1.01	6.020417	16.11	0	120.750000	360	59.58	...	66.61	29.817513	29.876557	29.935602	78	90.458333	97	55.29	59.985417	63.34
24	25	6.122773	0.0	5.75	12.827917	20.71	10	99.291667	360	54.39	...	61.83	29.906080	30.021709	30.083214	91	92.125000	94	53.64	56.187500	59.56
25	26	5.232935	0.0	4.61	11.187917	18.41	10	207.458333	320	47.39	...	57.83	29.787991	29.922071	30.024169	53	83.875000	96	42.44	49.020000	55.74
26	27	6.215040	0.0	0.00	5.137083	12.66	0	220.041667	350	42.82	...	70.27	29.758468	29.829814	29.906080	40	68.583333	87	42.73	44.944583	48.04
27	28	6.215040	0.0	0.00	4.935833	12.66	0	171.916667	346	37.42	...	74.53	29.758468	29.892549	29.965124	44	73.291667	90	43.39	48.276250	53.58
28	29	6.021597	0.0	5.75	11.412917	20.71	140	189.583333	240	62.02	...	84.81	29.640379	29.730176	29.817513	54	78.666667	94	53.78	64.081667	69.12
29	30	6.215040	0.0	3.00	15.830000	24.16	10	158.625000	360	39.38	...	74.71	29.728946	30.115196	30.348914	35	60.166667	86	28.36	40.511250	63.52

30 rows × 24 columns

In [ ]:
```
df_website_db
```

Out[ ]:

	Date	w_temp_max	w_temp_avg	w_temp_min	w_dew_point_max	w_dew_point_avg	w_dew_point_min	w_humidity_max	w_humidity_avg	w_humidity_min	w_wind_speed_max	w_wind_speed_avg	w_wind_speed_min	w_pressure_max	w_pressure_avg	w_pressure_min	w_precipitation
0	2022	66	60.8	55	62	59.5	55	100	95.7	75	7	2.4	0	29.6	29.6	29.5	0.05
1	2022	76	63.6	54	68	60.4	54	100	90.3	64	8	3.6	0	29.7	29.6	29.5	0.01
2	2022	84	74.6	69	70	68.7	65	100	83.2	53	20	12.2	7	29.5	29.4	29.3	0.00
3	2022	85	73.5	59	75	69.0	52	97	86.5	63	22	12.8	3	29.4	29.3	29.1	0.00
4	2022	71	59.4	50	55	49.5	42	100	73.0	42	12	5.2	0	29.4	29.3	29.3	0.41
5	2022	83	66.5	48	73	62.2	47	100	86.9	63	20	5.2	0	29.4	29.4	29.3	0.00
6	2022	84	74.9	68	75	71.3	67	100	89.4	58	12	4.9	0	29.6	29.5	29.5	0.00
7	2022	78	69.1	60	71	66.6	60	100	92.3	76	10	3.2	0	29.7	29.6	29.6	0.11
8	2022	81	71.2	64	69	67.0	64	100	87.6	58	16	6.2	0	29.6	29.5	29.4	0.02
9	2022	81	71.5	64	69	66.4	63	100	85.5	54	15	7.1	3	29.4	29.3	29.2	0.00
10	2022	79	60.2	43	69	55.6	31	100	85.1	60	24	12.9	0	29.6	29.3	29.2	0.00
11	2022	58	45.2	34	32	29.5	27	82	56.7	32	21	12.9	3	29.7	29.7	29.6	0.12
12	2022	58	45.1	29	35	27.5	20	96	56.3	23	9	5.4	0	29.7	29.6	29.5	0.00
13	2022	52	50.0	48	50	45.1	36	100	84.2	59	15	8.6	3	29.6	29.4	29.3	0.00
14	2022	50	43.7	40	43	36.0	33	89	74.7	59	17	11.2	5	29.8	29.7	29.6	0.19
15	2022	55	45.9	40	37	33.9	30	86	65.2	40	17	9.8	3	29.9	29.9	29.8	0.00
16	2022	58	49.4	40	41	35.5	28	97	62.6	34	6	2.5	0	29.9	29.8	29.7	0.00
17	2022	55	50.6	48	45	40.1	35	86	68.6	49	8	3.0	0	29.8	29.7	29.7	0.00
18	2022	47	40.4	37	41	36.6	32	97	86.7	70	20	13.2	6	29.9	29.8	29.7	0.03
19	2022	47	42.4	39	39	32.6	28	93	69.6	48	10	7.0	3	29.9	29.8	29.8	0.39
20	2022	45	43.6	41	44	41.0	36	100	90.6	82	9	5.2	0	29.8	29.8	29.8	0.03
21	2022	54	49.6	44	51	47.0	44	100	90.9	83	7	4.2	0	29.8	29.7	29.6	0.24
22	2022	65	58.8	53	61	52.7	47	96	81.3	60	7	2.9	0	29.6	29.5	29.4	0.02
23	2022	67	62.5	61	65	61.7	60	100	97.4	84	16	7.8	0	29.5	29.3	29.3	0.15
24	2022	61	57.5	55	60	56.3	54	100	95.8	90	21	11.9	6	29.6	29.5	29.4	0.18
25	2022	60	51.7	41	57	45.8	39	100	83.0	46	18	9.0	0	29.4	29.3	29.3	2.00
26	2022	71	54.8	43	47	43.5	40	100	70.4	34	13	4.6	0	29.4	29.3	29.3	0.00
27	2022	75	58.9	37	65	51.9	37	100	80.9	41	15	6.9	0	29.4	29.3	29.2	0.00
28	2022	82	69.8	52	69	64.5	52	100	85.0	51	21	10.2	0	29.4	29.2	29.1	0.00
29	2022	58	47.5	38	46	29.9	26	68	52.2	32	24	16.9	6	29.8	29.7	29.4	0.00

In [ ]:
```
print(df_kaggle_db)
```

	Date	k_temp_max	k_temp_avg	k_temp_min	k_dew_point_max	k_dew_point_avg	k_dew_point_min	k_humidity_max	k_humidity_avg	k_humidity_min	...	k_pressure_avg	k_pressure_min	k_visibility_max
0	1	68	58	47	43	39	37	71	54	37	...	30.34	30.28	10
1	2	75	62	48	52	45	39	80	61	41	...	30.26	30.18	10
2	4	75	67	58	69	63	57	100	87	73	...	30.09	30.01	10
3	5	59	57	55	58	56	54	100	97	93	...	30.16	30.08	10
4	6	63	59	55	56	51	46	93	75	56	...	30.28	30.22	10
5	7	71	60	48	49	41	34	80	53	26	...	30.19	30.06	10
6	8	75	62	48	52	47	41	93	67	41	...	30.10	30.04	10
7	9	74	61	47	45	43	40	86	59	31	...	30.07	29.92	10
8	10	76	63	49	61	53	43	93	70	46	...	29.83	29.74	10
9	11	65	54	42	62	41	29	93	67	40	...	30.03	29.78	10
10	12	51	44	36	29	23	16	64	50	36	...	30.34	30.25	10
11	13	41	36	31	17	13	9	58	43	27	...	30.52	30.46	10
12	14	45	38	30	23	17	12	58	44	30	...	30.40	30.30	10
13	15	48	44	40	47	39	23	100	72	43	...	30.14	30.03	10
14	16	50	42	34	49	45	28	100	91	82	...	30.00	29.92	10
15	17	53	42	30	27	21	14	82	52	22	...	30.40	30.25	10
16	18	56	43	30	27	23	19	78	51	24	...	30.48	30.42	10
17	19	69	51	33	45	38	23	86	64	42	...	30.27	30.17	10
18	20	70	57	44	63	57	43	100	85	70	...	30.08	30.02	10
19	21	74	68	62	69	65	62	100	90	79	...	30.05	29.99	10
20	22	67	63	58	64	62	56	100	97	93	...	29.86	29.70	10
21	23	81	67	53	57	48	39	100	62	23	...	29.64	29.51	10
22	24	66	53	40	39	32	19	76	47	18	...	30.06	29.88	10
23	25	67	53	38	38	33	25	85	53	20	...	30.26	30.20	10
24	26	77	60	42	37	33	27	62	40	18	...	30.22	30.14	10
25	27	64	53	42	37	33	27	76	52	27	...	30.45	30.37	10
26	28	72	57	42	54	45	35	82	62	41	...	30.24	30.09	10
27	29	73	65	56	61	57	52	93	75	57	...	30.02	29.95	10
28	30	79	72	64	63	62	59	87	71	54	...	30.03	29.97	10

```
    k_visibility_avg  k_visibility_min  k_wind_max  k_wind_avg  k_windgust  \
0                 10                10           9           5          14
1                 10                10          15           6          25
2                  8                 2          17           5          28
3                  6                 2          13           6          20
4                 10                 5          10           4          17
5                 10                10           7           2          11
6                 10                10          15           4          25
7                 10                10           8           3          13
8                 10                10          17           6          31
9                 10                 9          17           7          32
10                10                10          16           9          27
11                10                10          17           8          28
12                10                10           8           3          11
13                 5                 1          10           4          15
14                 4                 0          17           6          28
15                10                10          16           6          26
16                10                 3          10           2          15
17                10                10          13           3          22
18                 8                 0          12           3          16
19                 6                 0          13           5          20
20                 6                 0          20           7          28
21                10                10          16           5          27
22                10                10          15           5          28
23                10                10           9           3          16
24                10                10          10           3          17
25                10                10          10           4          16
26                10                10          14           4          24
27                10                10          16           7          31
28                10                10          15           7          28

    k_precipitationsum                 k_events
0                 0.00
1                 0.00
2                 0.56                    Rain
3                 1.51                    Rain
4                 0.04                    Rain
5                 0.00
6                 0.00
7                 0.00
8                 0.00
9                 0.00
10                0.00
11                0.00
12                0.00
13                0.02                    Rain
14                0.01               Fog , Rain
15                0.00
16                0.00
17                0.00
18                0.01               Fog , Rain
19                0.33               Fog , Rain
20                3.33  Fog , Rain , Thunderstorm
21                0.00
22                0.00
23                0.00
24                0.00
25                0.00
26                0.00
27                0.00
28                0.00

[29 rows x 21 columns]
```

In [ ]:
```
print(df_combined)
```

	Date	a_visibility_avg	a_snow_avg	a_wind_speed_min	a_wind_speed_avg	\
0	1	6.206132	0.0	0.00	4.679167	
1	2	5.920447	0.0	0.00	3.819583	
2	3	5.837088	0.0	3.44	10.071667	
3	4	6.063290	0.0	8.05	15.317500	
4	5	6.122773	0.0	0.00	5.559167	
5	6	6.215040	0.0	0.00	6.849583	
6	7	6.096048	0.0	0.00	5.571667	
7	8	5.956080	0.0	0.00	4.803750	
8	9	6.215040	0.0	3.44	7.270417	
9	10	6.104982	0.0	3.44	7.111250	
10	11	6.215040	0.0	1.99	9.574583	
11	12	6.215040	0.0	11.50	16.305833	
12	13	3.884400	0.0	4.00	7.507083	
13	14	5.637637	0.0	5.01	7.158333	
14	15	6.215040	0.0	9.22	12.482500	
15	16	6.215040	0.0	7.00	10.850000	
16	17	6.215040	0.0	1.01	4.482917	
17	18	6.215040	0.0	0.00	3.931667	
18	19	6.164466	0.0	1.99	12.100833	
19	20	6.215040	0.0	4.61	8.933750	
20	21	6.063290	0.0	1.99	5.083333	
21	22	4.968070	0.0	1.99	5.249167	
22	23	6.146649	0.0	0.00	3.501667	
23	24	3.528796	0.0	1.01	6.020417	
24	25	6.122773	0.0	5.75	12.827917	
25	26	5.232935	0.0	4.61	11.187917	
26	27	6.215040	0.0	0.00	5.137083	
27	28	6.215040	0.0	0.00	4.935833	
28	29	6.021597	0.0	5.75	11.412917	
29	30	6.215040	0.0	3.00	15.830000	

	a_wind_speed_max	a_wind_deg_min	a_wind_deg_avg	a_wind_deg_max	\
0	8.99	0	128.458333	360	
1	7.00	0	95.708333	221	
2	19.57	0	156.250000	190	
3	21.85	144	168.083333	190	
4	12.66	0	171.291667	357	
5	19.57	0	164.250000	230	
6	11.50	0	119.083333	200	
7	10.00	0	92.916667	180	
8	16.11	0	112.875000	180	
9	12.66	0	123.750000	200	
10	23.02	95	213.916667	350	
11	21.85	10	268.166667	360	
12	10.36	6	58.916667	350	
13	10.36	0	139.833333	360	
14	17.27	10	236.833333	360	
15	18.01	10	34.833333	58	
16	10.36	0	189.583333	350	
17	8.05	0	84.416667	180	
18	19.57	0	86.833333	360	
19	17.27	18	243.083333	360	
20	9.22	10	187.500000	360	
21	8.01	0	94.666667	360	
22	8.01	0	95.708333	330	
23	16.11	0	120.750000	360	
24	20.71	10	99.291667	360	
25	18.41	10	207.458333	320	
26	12.66	0	220.041667	350	
27	12.66	0	171.916667	346	
28	20.71	140	189.583333	240	
29	24.16	10	158.625000	360	

	a_temp_min	...	k_pressure_avg	k_pressure_min	k_visibility_max	\
0	55.42	...	30.34	30.28	10.0	
1	58.28	...	30.26	30.18	10.0	
2	68.58	...	NaN	NaN	NaN	
3	71.67	...	30.09	30.01	10.0	
4	50.02	...	30.16	30.08	10.0	
5	48.22	...	30.28	30.22	10.0	
6	69.03	...	30.19	30.06	10.0	
7	62.58	...	30.10	30.04	10.0	
8	66.45	...	30.07	29.92	10.0	
9	66.22	...	29.83	29.74	10.0	
10	45.39	...	30.03	29.78	10.0	
11	38.28	...	30.34	30.25	10.0	
12	32.02	...	30.52	30.46	10.0	
13	45.32	...	30.40	30.30	10.0	
14	37.38	...	30.14	30.03	10.0	
15	39.58	...	30.00	29.92	10.0	
16	39.22	...	30.40	30.25	10.0	
17	47.57	...	30.48	30.42	10.0	
18	36.28	...	30.27	30.17	10.0	
19	37.38	...	30.08	30.02	10.0	
20	39.38	...	30.05	29.99	10.0	
21	43.29	...	29.86	29.70	10.0	
22	50.58	...	29.64	29.51	10.0	
23	59.58	...	30.06	29.88	10.0	
24	54.39	...	30.26	30.20	10.0	
25	47.39	...	30.22	30.14	10.0	
26	42.82	...	30.45	30.37	10.0	
27	37.42	...	30.24	30.09	10.0	

```
28       62.02  ...           30.02           29.95              10.0
29       39.38  ...           30.03           29.97              10.0

    k_visibility_avg  k_visibility_min  k_wind_max  k_wind_avg  k_windgust  \
0               10.0              10.0         9.0         5.0        14.0
1               10.0              10.0        15.0         6.0        25.0
2                NaN               NaN         NaN         NaN         NaN
3                8.0               2.0        17.0         5.0        28.0
4                6.0               2.0        13.0         6.0        20.0
5               10.0               5.0        10.0         4.0        17.0
6               10.0              10.0         7.0         2.0        11.0
7               10.0              10.0        15.0         4.0        25.0
8               10.0              10.0         8.0         3.0        13.0
9               10.0              10.0        17.0         6.0        31.0
10              10.0               9.0        17.0         7.0        32.0
11              10.0              10.0        16.0         9.0        27.0
12              10.0              10.0        17.0         8.0        28.0
13              10.0              10.0         8.0         3.0        11.0
14               5.0               1.0        10.0         4.0        15.0
15               4.0               0.0        17.0         6.0        28.0
16              10.0              10.0        16.0         6.0        26.0
17              10.0               3.0        10.0         2.0        15.0
18              10.0              10.0        13.0         3.0        22.0
19               8.0               0.0        12.0         3.0        16.0
20               6.0               0.0        13.0         5.0        20.0
21               6.0               0.0        20.0         7.0        28.0
22              10.0              10.0        16.0         5.0        27.0
23              10.0              10.0        15.0         5.0        28.0
24              10.0              10.0         9.0         3.0        16.0
25              10.0              10.0        10.0         3.0        17.0
26              10.0              10.0        10.0         4.0        16.0
27              10.0              10.0        14.0         4.0        24.0
28              10.0              10.0        16.0         7.0        31.0
29              10.0              10.0        15.0         7.0        28.0

    k_precipitationsum                 k_events
0                 0.00
1                 0.00
2                  NaN                   None
3                 0.56                   Rain
4                 1.51                   Rain
5                 0.04                   Rain
6                 0.00
7                 0.00
8                 0.00
9                 0.00
10                0.00
11                0.00
12                0.00
13                0.00
14                0.02                   Rain
15                0.01              Fog , Rain
16                0.00
17                0.00
18                0.00
19                0.01              Fog , Rain
20                0.33              Fog , Rain
21                3.33  Fog , Rain , Thunderstorm
22                0.00
23                0.00
24                0.00
25                0.00
26                0.00
27                0.00
28                0.00
29                0.00

[30 rows x 62 columns]
```

Austin Weather Analysis

Introduction

In this study, we have used three different weather datasets for Austin weather analysis. These datasets were gathered from three different sources and formats (CSV, JSON, and HTML table).

Data Description:

First: Kaggle Austin weather analysis dataset in CSV format: This dataset is in CSV format and contains data for every date from 2013-12-21 to 2017-07-31. It has 1319 rows and 21 columns. For our analysis, we only used the Month of November in 2014 because it had fewer missing values as compared to other years. The following are attributes found in this dataset: link: https://www.kaggle.com/datasets/grubenm/austin-weather

Second: Austin weather captured from OpenWeatherMap in JSON format. It contains data from 2013-12-01 to 2022-12-08 with 82540 rows and 26 columns. link: https://home.openweathermap.org/history_forecast_bulks/new

Third: Austin weather from the Wunderground website for the month of Nov-2022 in HTML format. It consists of 19 different variables. For our analysis, we have used daily resolution for the month of November 2022. Totally it consists of 19 different attributes with 30 rows. For this purpose, we have used the BeautifulSoup library to be able to perform web scraping and convert the HTML format table into a pandas data frame. link: https://www.wunderground.com/history/monthly/us/tx/austin/KAUS/date/2022-11

Relationships

These datasets are connected to each other using the city name (Austin) and date (Month Nov). It is also worth mentioning that the JSON format file has been downloaded from OpenWeatherMap through the bulk history feature. There was no specific API to get these historical data through an API, however, we have an open API to get real-time/historical weather information from this website.

Data Clean-up

After data cleaning (handling missing data/transformation/header name change) of these datasets the final products were stored in an SQLite database for further analysis (Joining through a common key of date). In the end, we pulled these data out from the SQLite database and used a python visualization library called "Seaborn: graphical representation of weather information have plotted to provide visual insights.

Lessen learned

Data from different sources might be coming in different formats and metrics, for this, we need to be equipped well with the coding tools (pandas, scipy, numpy, ...) in order to be able to handle them appropriately. Web scraping was a more challenging part of data wrangling as the HTML tables have no specific standard format. Finally, after saving these datasets in an SQLite database I observed that the volume of storage has been reduced as compared to having them all in CSV formats.

Ethical Implications

In order to minimize the physical and emotional harm following steps have been taken:

- Reference links are provided in case one might need to validate the results.
- The transformation has been clearly outlined in each milestone and efforts spent to minimize the error rate and reflect reality.
- Formulas for conversion have already been validated.

Conclusion

Insights provided through the line and bar graphs show that there is a strong correlation between data coming from OpenWeatherMap and from the website as both are referring to the same year and month Nov 2022, however, the difference between them and Kaggle is because Kaggle data represents weather info for Nov 2014. This in turn shows that Nov 2014 was colder than Nov 2022 in this city. On the other hand, we see that metrics: Temperature, Wind speed, Humidity, and Atmospheric Temperature in 2014 Austin has a lower value compared to 2022, except for Pressure.

Finally, overall Data wrangling (Gathering, cleaning, transformation, saving,...) is almost 90% of a data science task to prepare an accurate and reliable data source for the final analysis. The steps must be documented well so one can understand how data was gathered and transformed.

In [ ]: