Assignment_4

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Task 4P: Working with pandas Data Frames (Heterogeneous Data)

Name: Prateek Singh

Student number: 221218743

Email: singhprate@deakin.edu.au

Unit: SIT731 This task allows us to process weather data which contains hourly meteorological data for three airports in New York: LGA, JFK, and EWR for the year 2013. This allows us to explore the Pandas library to modify, process, and visualise heterogeneous data. This task also shows how to handle missing/noisy data, which is how the data is encountered in real world.

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import numpy as np
```

1. Convert all columns so that they use metric (International System of Units, SI) or derived units: temp and dewp to Celsius, precip to millimetres, visib to kilometres, as well as wind_speed and wind_gust to km/h. Replace the data in-place (overwrite existing columns with new ones).

[2]:
```
#Utility function to change all the columns to SI values
def DFToSI(_df):
    df['temp'] = (df['temp'] - 32) * 5/9
    df['dewp'] = (df['dewp'] - 32) * 5/9
    df['precip'] = df['precip'] * 25.4
    df['visib'] = df['visib'] * 1.60934
    df['wind_speed'] = df['wind_speed'] * 1.60934
    df['wind_gust'] = df['wind_gust'] * 1.60934
    return df

df = pd.read_csv("Resource_Data/weather.csv", comment="#")
df = DFToSI(df)
display(df)
```

```
      origin  year  month  day  hour  temp  dewp  humid  wind_dir  wind_speed  \
0        EWR  2013      1    1     0   2.8  -5.6  53.97     230.0   16.667967
```

```
1         EWR  2013      1    1     1   2.8  -5.6  53.97     230.0   22.223955
2         EWR  2013      1    1     2   3.3  -5.6  52.09     230.0   20.371959
3         EWR  2013      1    1     3   3.3  -5.0  54.51     230.0   22.223955
4         EWR  2013      1    1     4   3.3  -4.4  57.04     240.0   24.075952
…       …   …    …  …    …    …   …     …        …         …
26125     LGA  2013     12   30    19   2.2  -6.7  51.78     340.0   22.223955
26126     LGA  2013     12   30    20   1.1  -8.3  49.51     330.0   27.779944
26127     LGA  2013     12   30    21   0.0  -9.4  49.19     340.0   24.075952
26128     LGA  2013     12   30    22  -0.6 -10.6  46.74     320.0   27.779944
26129     LGA  2013     12   30    23  -1.7 -11.7  46.41     330.0   29.631941

       wind_gust  precip  pressure    visib            time_hour
0      19.181163     0.0    1013.9  16.0934  2013-01-01 01:00:00
1      25.574883     0.0    1013.0  16.0934  2013-01-01 02:00:00
2      23.443643     0.0    1012.6  16.0934  2013-01-01 03:00:00
3      25.574883     0.0    1012.7  16.0934  2013-01-01 04:00:00
4      27.706124     0.0    1012.8  16.0934  2013-01-01 05:00:00
…           …     …        …       …                  …
26125  25.574883     0.0    1017.1  16.0934  2013-12-30 20:00:00
26126  31.968604     0.0    1018.8  16.0934  2013-12-30 21:00:00
26127  27.706124     0.0    1019.5  16.0934  2013-12-30 22:00:00
26128  31.968604     0.0    1019.9  16.0934  2013-12-30 23:00:00
26129  34.099845     0.0    1020.9  16.0934  2013-12-31 00:00:00

[26130 rows x 15 columns]
```

2. Convert the time_hour column (in-place) to the datetime64 type and then subtract one hour so that data match the information stored in the month, day, and hour fields.

[3]:
```
df['time_hour'] = pd.to_datetime(df['time_hour'])
df['time_hour'] = df['time_hour'] - pd.Timedelta(hours=1)
```

3. Compute daily mean temperatures (360+ average temperatures for each day separately) for the JFK airport with missing hourly temperature measurements ignored (removed) whatsoever (e.g.,mean of [10, NaN, 20] is simply 15).

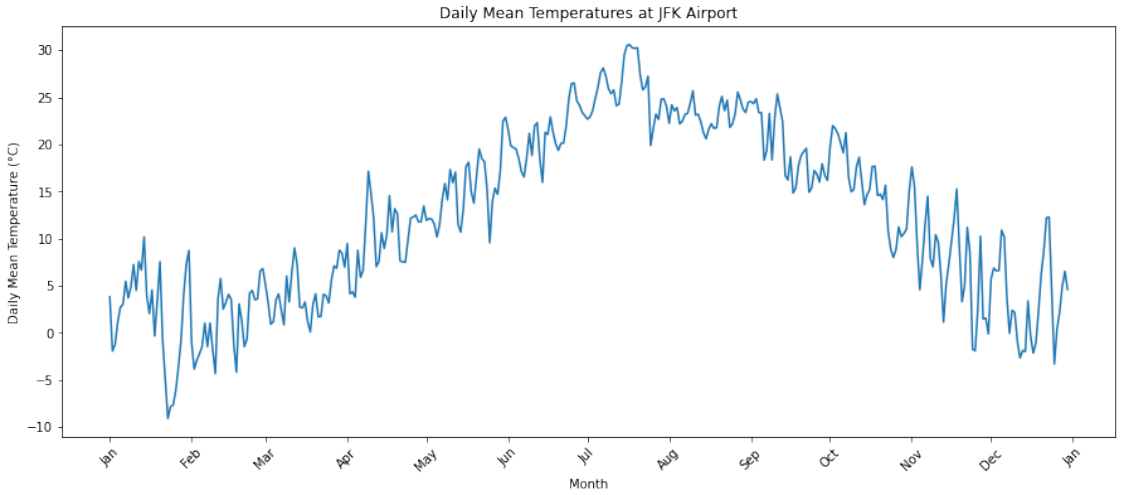
[4]:
```
jfk_df = df[df['origin'] == 'JFK']
#jfk_df = jfk_df.dropna(subset=['temp'])
jfk_daily_mean = jfk_df.groupby(jfk_df['time_hour'].dt.date)['temp'].mean().
 ↪dropna()
print(jfk_daily_mean)
```

```
time_hour
2013-01-01    3.817391
2013-01-02   -1.920833
2013-01-03   -1.237500
2013-01-04    1.129167
2013-01-05    2.720833
                …
```

```
2013-12-26    0.383333
2013-12-27    2.220833
2013-12-28    4.966667
2013-12-29    6.533333
2013-12-30    4.620833
Name: temp, Length: 364, dtype: float64
```

4. Present the daily mean temperatures (360+ data points) in a single plot. The x-axis labels should be human-readable and intuitive (e.g., month names).

[5]:
```
plt.figure(figsize=(15, 6))
plt.plot(jfk_daily_mean.index, jfk_daily_mean, label='JFK')
# Set the x-axis labels to be month names
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%b'))
plt.gca().xaxis.set_major_locator(mdates.MonthLocator())
plt.xticks(rotation=45)
plt.xlabel('Month')
plt.ylabel('Daily Mean Temperature (°C)')
plt.title('Daily Mean Temperatures at JFK Airport')
plt.show()
```



5. Find the five hottest days.

[6]:
```
num_days = 5
five_hottest_days = df.groupby(df["time_hour"].dt.date)["temp"].mean().
  ↪sort_values(ascending=False).head(num_days)
print(five_hottest_days)
```

```
time_hour
2013-07-19    32.233333
2013-07-18    31.395833
2013-07-20    30.912500
```

```
2013-07-17    30.719444
2013-07-16    30.548611
Name: temp, dtype: float64
```

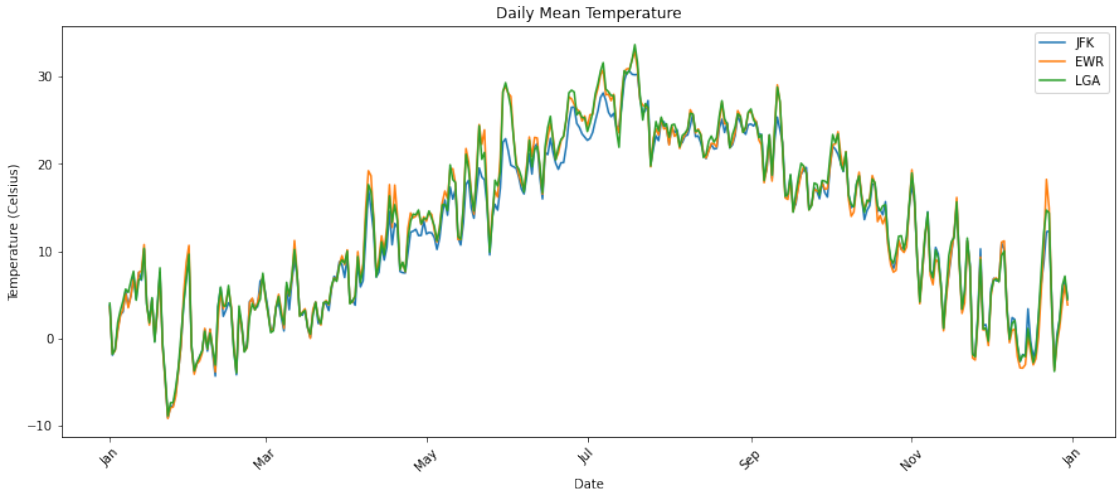
2. Additional Tasks for Postgraduate (SIT731) Students (*)

1. Compute the daily mean temperatures also for the EWR and LGA airports.

[7]:
```
ewr_df = df[df['origin'] == 'EWR']
ewr_df = ewr_df.dropna(subset=['temp'])
ewr_daily_mean = ewr_df.groupby(ewr_df['time_hour'].dt.date)['temp'].mean().
 ↪dropna()

# Compute daily mean temperatures for LGA
lga_df = df[df['origin'] == 'LGA']
lga_df = lga_df.dropna(subset=['temp'])
lga_daily_mean = lga_df.groupby(lga_df['time_hour'].dt.date)['temp'].mean().
 ↪dropna()
```

2. Draw the daily mean temperatures for the three airports in the same plot (three curves of differentcolours). Add a readable legend.

[8]:
```
# Plot the daily mean temperatures for JFK, EWR, and LGA
plt.figure(figsize=(15, 6))

jfk_daily_mean.plot(label='JFK')
ewr_daily_mean.plot(label='EWR')
lga_daily_mean.plot(label='LGA')

plt.xlabel("Date")
# Define the x-axis format
ax = plt.gca()
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b'))
plt.xticks(rotation=45)

plt.ylabel("Temperature (Celsius)")
plt.title("Daily Mean Temperature")

plt.legend()
plt.show()
```

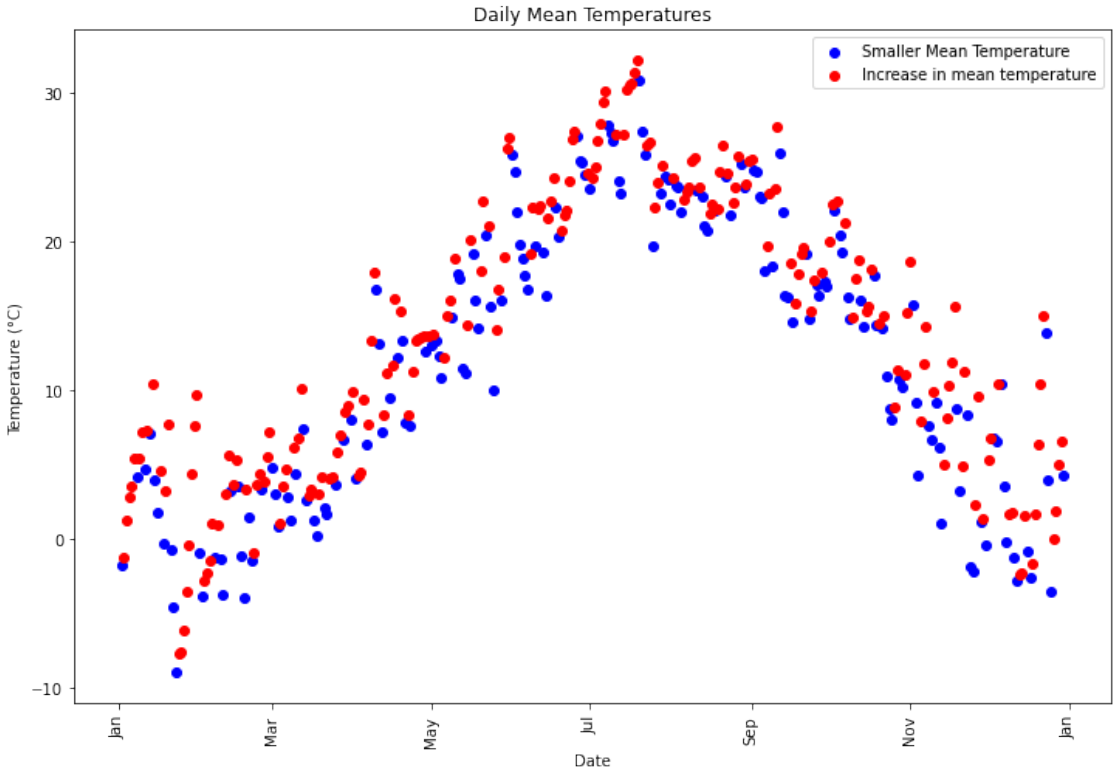


3. Optional Features (**)

1. Mark the days with greater mean temperature than in the preceding day in red and those with smaller – in blue (in the plot).

[9]:
```
df_daily_mean = df.groupby(df["time_hour"].dt.date)["temp"].mean().dropna()
df_daily_mean = df_daily_mean.reset_index()
df_daily_mean.columns = ["date", "mean_temp"]

plt.figure(figsize=(12, 8))

df_daily_mean["temp_diff"] = df_daily_mean["mean_temp"].diff()

plt.scatter(df_daily_mean[df_daily_mean["temp_diff"] <= 0]["date"],
            df_daily_mean[df_daily_mean["temp_diff"] <= 0]["mean_temp"],
            color='blue',
            label="Smaller Mean Temperature")

plt.scatter(df_daily_mean[df_daily_mean["temp_diff"] > 0]["date"],
            df_daily_mean[df_daily_mean["temp_diff"] > 0]["mean_temp"],
            color='red',
            label="Increase in mean temperature")

plt.xlabel("Date")
# Define the x-axis format
ax = plt.gca()
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b'))
plt.xticks(rotation=45)

plt.ylabel('Temperature (°C)')
```

```
plt.title('Daily Mean Temperatures')
plt.legend()
plt.xticks(rotation=90)

plt.show()
```



2. For the JFK airport, list all missing temperature readings. This should include not only the temperatures explicitly marked as missing values, but also the records that were completely omitted, for instance 2013-02-21 06:00:00.

[10]:
```
### To find the missing data I'm assuming that hourly data which is not present␣
 ↪has to be inserted
### All the other values are null and missing hours are inserted into th␣
 ↪dataframe (Done in the follwoing cell)
all_hours = pd.DataFrame(pd.date_range(start=jfk_df["time_hour"].min(),
                                       end=jfk_df["time_hour"].max(),
                                       freq="H"),
                         columns=["time_hour"])

missing_temperature_readings = all_hours[~all_hours["time_hour"].
 ↪isin(jfk_df["time_hour"])]
```

```
#Just display here, populate in next cell
display(missing_temperature_readings)
```

```
               time_hour
5    2013-01-01 05:00:00
1229 2013-02-21 05:00:00
1518 2013-03-05 06:00:00
2137 2013-03-31 01:00:00
2208 2013-04-03 00:00:00
5380 2013-08-13 04:00:00
5452 2013-08-16 04:00:00
5541 2013-08-19 21:00:00
5614 2013-08-22 22:00:00
5616 2013-08-23 00:00:00
5617 2013-08-23 01:00:00
7152 2013-10-26 00:00:00
7153 2013-10-26 01:00:00
7154 2013-10-26 02:00:00
7155 2013-10-26 03:00:00
7156 2013-10-26 04:00:00
7177 2013-10-27 01:00:00
7303 2013-11-01 07:00:00
7304 2013-11-01 08:00:00
7344 2013-11-03 00:00:00
7345 2013-11-03 01:00:00
7346 2013-11-03 02:00:00
7347 2013-11-03 03:00:00
7348 2013-11-03 04:00:00
7383 2013-11-04 15:00:00
```

3. Add the missing records to the dataset (just the date-time information, with all the remaining fields being set to NaN).

[11]:
```
date_range = pd.date_range(start='2013-01-01', end='2013-12-31', freq='H')
df_complete = pd.DataFrame({'time_hour': date_range})
df_merged = pd.merge(df_complete, df, how='left', on='time_hour')
display(df_merged)
```

```
                time_hour origin    year  month   day  hour  temp  dewp  \
0     2013-01-01 00:00:00    EWR  2013.0    1.0   1.0   0.0   2.8  -5.6
1     2013-01-01 00:00:00    JFK  2013.0    1.0   1.0   0.0   3.3  -5.0
2     2013-01-01 00:00:00    LGA  2013.0    1.0   1.0   0.0   3.9  -7.2
3     2013-01-01 01:00:00    EWR  2013.0    1.0   1.0   1.0   2.8  -5.6
4     2013-01-01 01:00:00    JFK  2013.0    1.0   1.0   1.0   3.3  -4.4
…                     …    …      …    …   …   …   …   …
26144 2013-12-30 22:00:00    LGA  2013.0   12.0  30.0  22.0  -0.6 -10.6
26145 2013-12-30 23:00:00    EWR  2013.0   12.0  30.0  23.0  -1.7 -11.1
26146 2013-12-30 23:00:00    JFK  2013.0   12.0  30.0  23.0  -1.1 -12.2
26147 2013-12-30 23:00:00    LGA  2013.0   12.0  30.0  23.0  -1.7 -11.7
```

```
26148 2013-12-31 00:00:00    NaN     NaN    NaN   NaN   NaN   NaN   NaN

       humid  wind_dir  wind_speed  wind_gust  precip  pressure    visib
0      53.97     230.0   16.667967  19.181163     0.0    1013.9  16.0934
1      54.51     240.0   25.927948  29.837364     0.0    1014.4  16.0934
2      44.18     240.0   22.223955  25.574883     0.0    1013.7  16.0934
3      53.97     230.0   22.223955  25.574883     0.0    1013.0  16.0934
4      57.04     250.0   27.779944  31.968604     0.0    1013.5  16.0934
…      …       …         …          …          …       …
26144  46.74     320.0   27.779944  31.968604     0.0    1019.9  16.0934
26145  48.69     330.0   24.075952  27.706124     0.0    1021.1  16.0934
26146  42.66     340.0   29.631941  34.099845     0.0    1020.9  16.0934
26147  46.41     330.0   29.631941  34.099845     0.0    1020.9  16.0934
26148    NaN       NaN         NaN        NaN     NaN       NaN     NaN

[26149 rows x 15 columns]
```

4. Re-compute the daily average temperatures, this time by linearly interpolating between the preceding and following non-missing data, e.g., a temperature sequence of [..., 10, NaN, NaN, 40, ...] should be transformed to [..., 10, 20, 30, 40, ...].

[12]:
```
df_interpolated = df_merged.copy() #Creating a new df from original to preserve␣
 ↪original data
df_interpolated['temp'] = df_interpolated['temp'].interpolate(method="linear")
display(df_interpolated)
```

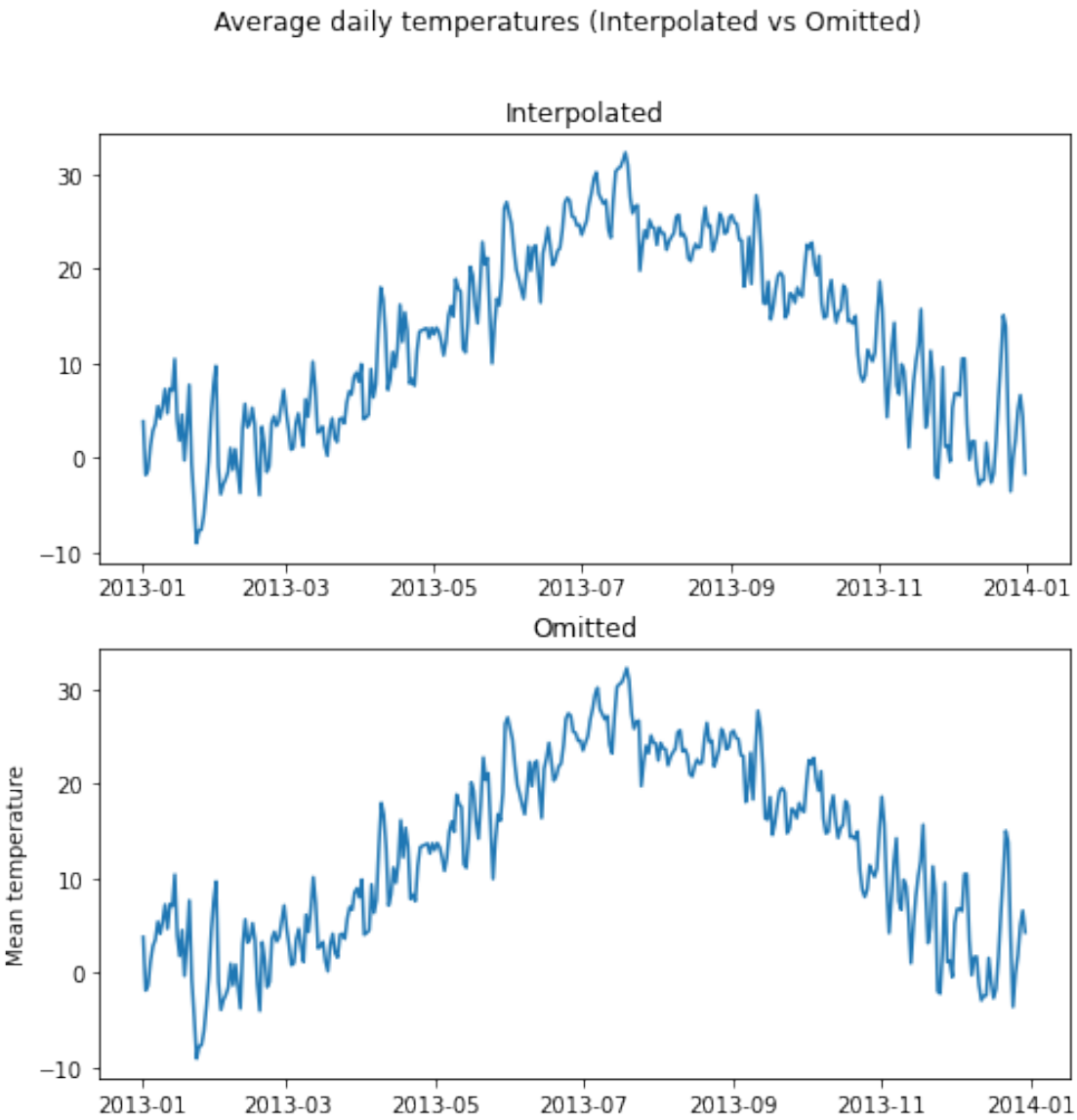
```
                time_hour origin    year  month   day  hour  temp  dewp  \
0     2013-01-01 00:00:00    EWR  2013.0    1.0   1.0   0.0   2.8  -5.6
1     2013-01-01 00:00:00    JFK  2013.0    1.0   1.0   0.0   3.3  -5.0
2     2013-01-01 00:00:00    LGA  2013.0    1.0   1.0   0.0   3.9  -7.2
3     2013-01-01 01:00:00    EWR  2013.0    1.0   1.0   1.0   2.8  -5.6
4     2013-01-01 01:00:00    JFK  2013.0    1.0   1.0   1.0   3.3  -4.4
…                     …    …      …    …   …     …     …     …
26144 2013-12-30 22:00:00    LGA  2013.0   12.0  30.0  22.0  -0.6 -10.6
26145 2013-12-30 23:00:00    EWR  2013.0   12.0  30.0  23.0  -1.7 -11.1
26146 2013-12-30 23:00:00    JFK  2013.0   12.0  30.0  23.0  -1.1 -12.2
26147 2013-12-30 23:00:00    LGA  2013.0   12.0  30.0  23.0  -1.7 -11.7
26148 2013-12-31 00:00:00    NaN     NaN    NaN   NaN   NaN  -1.7   NaN

       humid  wind_dir  wind_speed  wind_gust  precip  pressure    visib
0      53.97     230.0   16.667967  19.181163     0.0    1013.9  16.0934
1      54.51     240.0   25.927948  29.837364     0.0    1014.4  16.0934
2      44.18     240.0   22.223955  25.574883     0.0    1013.7  16.0934
3      53.97     230.0   22.223955  25.574883     0.0    1013.0  16.0934
4      57.04     250.0   27.779944  31.968604     0.0    1013.5  16.0934
…      …       …         …          …          …       …
26144  46.74     320.0   27.779944  31.968604     0.0    1019.9  16.0934
26145  48.69     330.0   24.075952  27.706124     0.0    1021.1  16.0934
```

```
26146  42.66     340.0   29.631941  34.099845     0.0    1020.9  16.0934
26147  46.41     330.0   29.631941  34.099845     0.0    1020.9  16.0934
26148    NaN       NaN         NaN        NaN     NaN       NaN      NaN

[26149 rows x 15 columns]
```

5. Draw a plot of average daily temperatures comparing the missing value-omitted vs linearly interpolated cases.

[13]:
```
interpolated_mean_temp = df_interpolated.groupby(df_interpolated["time_hour"].
↪dt.date).mean()["temp"]
omitted_mean_temp = df.groupby(df["time_hour"].dt.date)["temp"].mean().dropna()

plt.figure(figsize=(15, 6))
fig, (ax1, ax2) = plt.subplots(2, figsize=(8, 8))
fig.suptitle("Average daily temperatures (Interpolated vs Omitted)")


ax1.set_title("Interpolated")
ax1.plot(interpolated_mean_temp, label="Interpolated")
ax2.set_title('Omitted')
ax2.plot(omitted_mean_temp, label="Omitted")

plt.ylabel("Mean temperature")
plt.show()
```

```
<Figure size 1080x432 with 0 Axes>
```


Average daily temperatures (Interpolated vs Omitted)
Interpolated
Omitted
Mean temperature
30
20
10
0
−10
2013-01
2013-03
2013-05
2013-07
2013-09
2013-11
2014-01