CodeReport

January 2, 2025

1 Common Task: Miami, FL

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2.1 Initial Data Gathering

2.1.1 National Weather Service

[ ]:
```
response = requests.get("https://api.weather.gov/points/25.7617,-80.1918",␣
↪headers={"User-Agent": ""})
if response.status_code == 200:
    data = response.json()
    office = data['properties']['cwa']
    gridX = data['properties']['gridX']
    gridY = data['properties']['gridY']
    print(data)

# Fetch the hourly forecast using the grid information
hourly_forecast_url = f"https://api.weather.gov/gridpoints/{office}/
↪{gridX},{gridY}/forecast/hourly"
response = requests.get(hourly_forecast_url, headers={"User-Agent": ""})
if response.status_code == 200:
    hourly_data = response.json()
    # Process the hourly_data
    print(hourly_data)
    #store to json file
    with open('data.json', 'w') as outfile:
        json.dump(hourly_data, outfile)
def remove_alphabetical_columns_from_json(json_data):
    """
    Remove columns from a JSON object that contain only alphabetical characters.
    """
    # Load the JSON data into a Python object
    python_data = json.loads(json_data)

    # Convert the Python object to a DataFrame
    df = pd.DataFrame(python_data)
```

```python
    # Identify columns to remove
    cols_to_remove = []
    for col in df.columns:
        if df[col].apply(lambda x: str(x).isalpha()).all():
            cols_to_remove.append(col)

    # Drop identified columns
    df_cleaned = df.drop(columns=cols_to_remove)

    # Convert the cleaned DataFrame back to JSON
    cleaned_json = df_cleaned.to_json(orient='records')

    return cleaned_json

def remove_non_numerical_from_json_automatic(json_data):
    """
    Remove non-numerical characters from columns that contain mixed data types␣
 ↪in a JSON object.

    Returns:
        str: The cleaned JSON-formatted data.
    """
    # Load the JSON data into a Python object
    python_data = json.loads(json_data)

    # Convert the Python object to a DataFrame
    df = pd.DataFrame(python_data)

    # Automatically identify columns to clean
    columns_to_clean = []
    for col in df.columns:
        if df[col].apply(lambda x: any(char.isdigit() for char in str(x)) and␣
 ↪any(char.isalpha() for char in str(x))).any():
            columns_to_clean.append(col)

    # Remove non-numerical characters from identified columns
    for col in columns_to_clean:
        df[col] = df[col].apply(lambda x: float(re.sub('[^0-9.]', '', str(x))))

    # Convert the cleaned DataFrame back to JSON
    cleaned_json = df.to_json(orient='records')

    return cleaned_json

def process_weather_data(json_data):
    processed_data = []
    for period in json_data['properties']['periods']:
```

```
        data_point = {
            "timestamp": period.get("startTime", None),
            "temperature": period.get("temperature", None),
            "temperatureUnit": period.get("temperatureUnit", None),
            "windSpeed": period.get("windSpeed", None),
            "windDirection": period.get("windDirection", None),
            "dewpoint": period.get("dewpoint", None),
            "probabilityOfPrecipitation": period.
 ↪get("probabilityOfPrecipitation", None),
            "relativeHumidity": period.get("relativeHumidity", None),
        }
        processed_data.append(data_point)
    return remove_alphabetical_columns_from_json(json.dumps(processed_data))


# Load the JSON data from the file (assuming the file name is 'data.json')
with open('data.json', 'r') as infile:
    raw_data = json.load(infile)

# Process the data
processed_data =␣
 ↪remove_non_numerical_from_json_automatic(process_weather_data(raw_data))

# Optionally, save the processed data to another JSON file
with open('processed_data.json', 'w') as outfile:
    json.dump(processed_data, outfile)
```

2.1.2 Open Mateo Historical Weather Data

[43]:

```
# Define the start and end parameters in the correct format
start_time = "2015-01-01"
end_time = "2023-09-20"


# Build the API URL
api_url = f"https://archive-api.open-meteo.com/v1/archive?latitude=25.
 ↪7934&longitude=-80.
 ↪29&start_date={start_time}&end_date={end_time}&hourly=temperature_2m,relativehumidity_2m,de
# Make the API request
response = requests.get(api_url)

# Check the response
if response.status_code == 200:
    json_data = response.json()
    #save data
    hourly_df = pd.DataFrame(json_data['hourly'])
    #save to a file
```

```
    hourly_df.to_csv('MateoData.csv')
else:
    print("Failed:", response.json())
```

[3]:

```
#last 10 rows
hourly_df = pd.read_csv('MateoData.csv')
hourly_df.tail(10)
```

[3]:

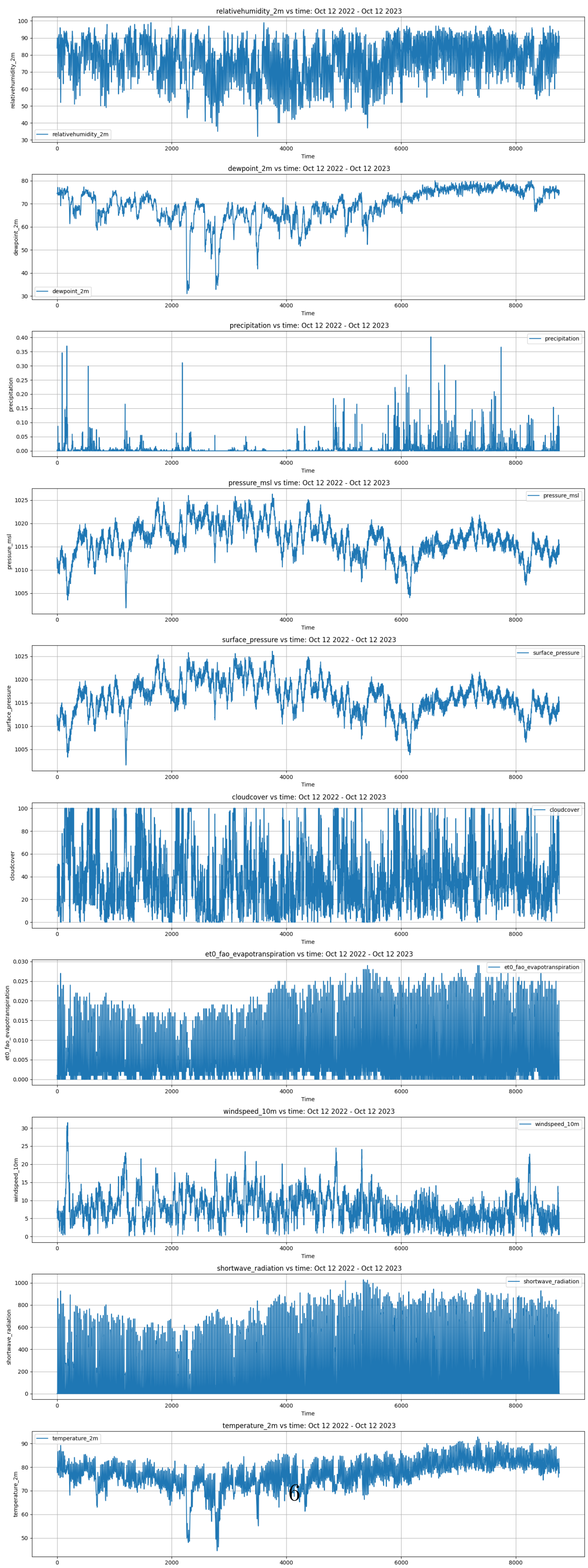
```
       Unnamed: 0              time  temperature_2m  relativehumidity_2m  \
76430       76430  2023-09-20T14:00            80.1                   81
76431       76431  2023-09-20T15:00            83.6                   78
76432       76432  2023-09-20T16:00            81.6                   82
76433       76433  2023-09-20T17:00            81.3                   82
76434       76434  2023-09-20T18:00            81.2                   82
76435       76435  2023-09-20T19:00            80.6                   84
76436       76436  2023-09-20T20:00            79.2                   89
76437       76437  2023-09-20T21:00            77.8                   91
76438       76438  2023-09-20T22:00            77.4                   91
76439       76439  2023-09-20T23:00            77.8                   90

       dewpoint_2m  precipitation  pressure_msl  surface_pressure  cloudcover  \
76430         73.8          0.055        1015.2            1015.0          62
76431         75.9          0.087        1014.6            1014.4          88
76432         75.4          0.083        1014.0            1013.8          79
76433         75.2          0.016        1013.3            1013.1          71
76434         75.4          0.000        1013.7            1013.5          56
76435         75.5          0.000        1013.8            1013.6          41
76436         75.6          0.020        1014.4            1014.2          62
76437         75.0          0.083        1015.3            1015.1          46
76438         74.5          0.031        1015.4            1015.2          37
76439         74.5          0.000        1015.5            1015.3          25

       et0_fao_evapotranspiration  windspeed_10m  shortwave_radiation
76430                       0.011            4.9                390.0
76431                       0.020            5.3                738.0
76432                       0.013            6.8                453.0
76433                       0.008            5.7                254.0
76434                       0.004            4.5                127.0
76435                       0.002            4.0                 61.0
76436                       0.001            3.5                  3.0
76437                       0.000            1.1                  0.0
76438                       0.000            0.5                  0.0
76439                       0.000            2.2                  0.0
```

[9]:

```
df = hourly_df
columns_to_plot = ['relativehumidity_2m', 'dewpoint_2m', 'precipitation',␣
↪'pressure_msl', 'surface_pressure',
```

```
                    'cloudcover', 'et0_fao_evapotranspiration', 'windspeed_10m',␣
↪'shortwave_radiation', 'temperature_2m']
df = df.tail(365*24)
#make column time go from 0 to the last row
df['time'] = range(0, len(df))
# Creating subplots
fig, axes = plt.subplots(nrows=len(columns_to_plot), figsize=(15, 4 *␣
↪len(columns_to_plot)))

for i, column in enumerate(columns_to_plot):
    axes[i].plot(df['time'], df[column], label=column)
    axes[i].set_title(f" {column} vs time: Oct 12 2022 - Oct 12 2023")
    axes[i].set_xlabel("Time")
    axes[i].set_ylabel(column)
    axes[i].grid(True)
    axes[i].legend()

plt.tight_layout()
# Uncomment the below line to save the plot as an image
# plt.savefig("temperature_vs_other_variables_separate.png")
plt.show()
```

```
/var/folders/qg/3x6_knhn5gx0412ktn3vq36c0000gn/T/ipykernel_60188/1478926394.py:6
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['time'] = range(0, len(df))
```


relativehumidity_2m vs time: Oct 12 2022 - Oct 12 2023
relativehumidity_2m
Time
dewpoint_2m vs time: Oct 12 2022 - Oct 12 2023
dewpoint_2m
Time
precipitation vs time: Oct 12 2022 - Oct 12 2023
precipitation
Time
pressure_msl vs time: Oct 12 2022 - Oct 12 2023
pressure_msl
Time
surface_pressure vs time: Oct 12 2022 - Oct 12 2023
surface_pressure
Time
cloudcover vs time: Oct 12 2022 - Oct 12 2023
cloudcover
Time
et0_fao_evapotranspiration vs time: Oct 12 2022 - Oct 12 2023
et0_fao_evapotranspiration
Time
windspeed_10m vs time: Oct 12 2022 - Oct 12 2023
windspeed_10m
Time
shortwave_radiation vs time: Oct 12 2022 - Oct 12 2023
shortwave_radiation
Time
temperature_2m vs time: Oct 12 2022 - Oct 12 2023
temperature_2m
Time

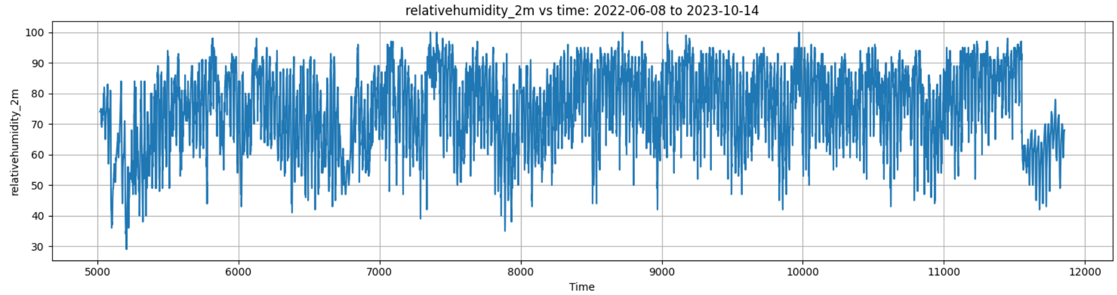
2.1.3 Open Mateo Forecast Data

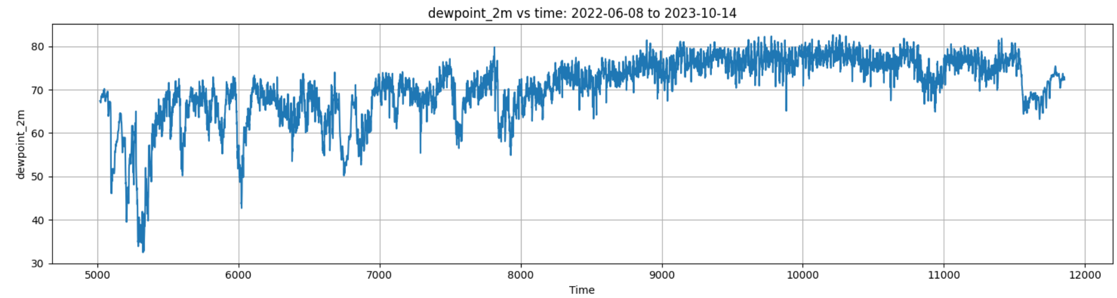
[5]:
```
# Build the API URL
api_url = f"https://api.open-meteo.com/v1/forecast?latitude=25.
↪7934&longitude=-80.
↪29&hourly=temperature_2m,relativehumidity_2m,dewpoint_2m,precipitation,windspeed_10m,shortw
# Make the API request
response = requests.get(api_url)

# Check the response
if response.status_code == 200:
    json_data = response.json()
    #save data
    Forecastdf = pd.DataFrame(json_data['hourly'])

    Forecastdf[['date_local', 'time_local']] = Forecastdf['time'].str.
↪split('T', expand=True)
    Forecastdf[['year', 'month', 'day']] = Forecastdf['date_local'].str.
↪split('-', expand=True)
    # drop time and date_local
    Forecastdf.drop(columns=['time', 'date_local'], inplace=True)
    #format time by removing :00
    Forecastdf['time_local'] = Forecastdf['time_local'].str.replace(':00', '')
    #save file
    Forecastdf.to_csv('ForecastData.csv')
else:
    print("Failed:", response.json())
```

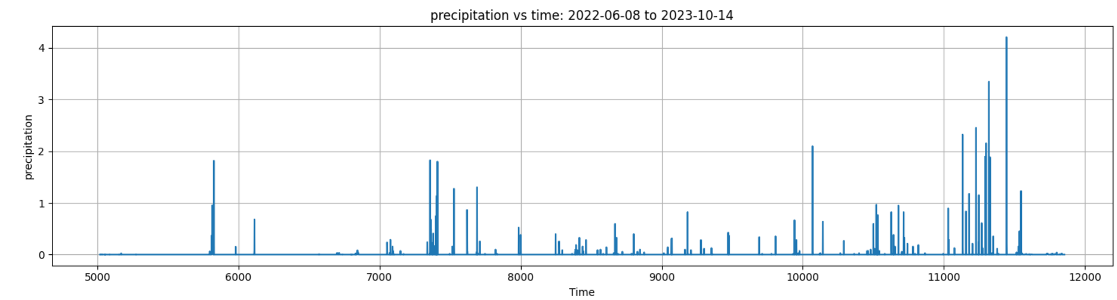
[34]:
```
Forecastdf = pd.read_csv('ForecastData.csv')
```

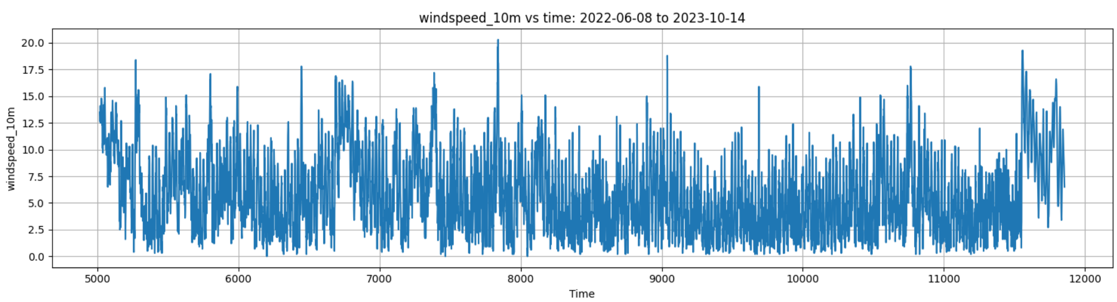
[7]:
```
df = pd.read_csv('ForecastData.csv')
columns_to_plot = ['relativehumidity_2m', 'dewpoint_2m', 'precipitation',␣
↪'windspeed_10m', 'shortwave_radiation']

# Creating subplots
fig, axes = plt.subplots(nrows=len(columns_to_plot), figsize=(15, 4 *␣
↪len(columns_to_plot)))

for i, column in enumerate(columns_to_plot):
    axes[i].plot(df['time'], df[column], label=column)
    axes[i].set_title(f"{column} vs time: 2022-06-08 to 2023-10-14")
    axes[i].set_xlabel("Time")
    axes[i].set_ylabel(column)
    axes[i].grid(True)
```

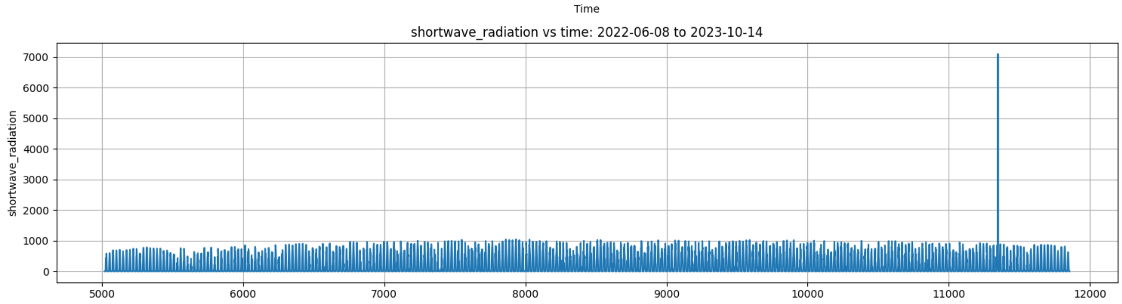
```python
plt.tight_layout()
# Uncomment the below line to save the plot as an image
# plt.savefig("temperature_vs_other_variables_separate.png")

plt.show()
```


relativehumidity_2m vs time: 2022-06-08 to 2023-10-14
relativehumidity_2m
Time
100
90
80
70
60
50
40
30
5000
6000
7000
8000
9000
10000
11000
12000


dewpoint_2m vs time: 2022-06-08 to 2023-10-14
dewpoint_2m
Time
80
70
60
50
40
30
5000
6000
7000
8000
9000
10000
11000
12000


precipitation vs time: 2022-06-08 to 2023-10-14
precipitation
Time
4
3
2
1
0
5000
6000
7000
8000
9000
10000
11000
12000


windspeed_10m vs time: 2022-06-08 to 2023-10-14
windspeed_10m
Time
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
5000
6000
7000
8000
9000
10000
11000
12000

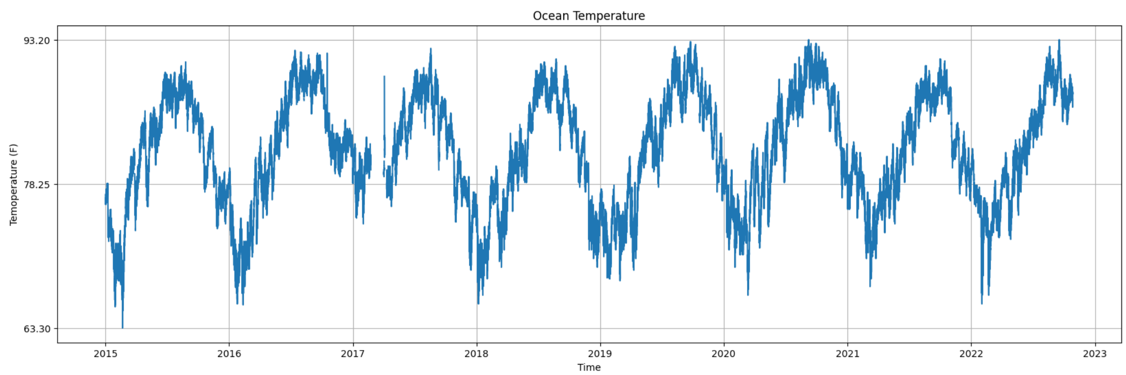

shortwave_radiation vs time: 2022-06-08 to 2023-10-14
shortwave_radiation
Time
7000
6000
5000
4000
3000
2000
1000
0
5000
6000
7000
8000
9000
10000
11000
12000

2.1.4 NOAA Ocean Water Temperature

[84]:
```
# NOAA Ocean Temp API
oceandf = pd.DataFrame()

for i in range(2015, 2024):  # Looping from 2015 to 2023
    start_time = f"{i}0101"
    end_time = f"{i}1231" if i != 2023 else "20230920"

    api_url = f"https://api.tidesandcurrents.noaa.gov/api/prod/datagetter?
↪product=water_temperature&application=NOS.COOPS.TAC.
↪PHYSOCEAN&begin_date={start_time}&end_date={end_time}&station=8723214&time_zone=GMT&units=e

    response = requests.get(api_url)

    if response.status_code == 200:
        json_data = response.json()
        hourly_df = pd.DataFrame(json_data['data'])

        # Remove column 'f' if it exists
        if 'f' in hourly_df.columns:
            hourly_df = hourly_df.drop(columns=['f'])

        # Append this year's data to the master DataFrame
        oceandf = pd.concat([oceandf, hourly_df], ignore_index=True)

    else:
        print(f"Failed for year {i}: ", response.json())

#change column name v to temp(f)
oceandf = oceandf.rename(columns={'v': 'temp(f)'})
#check how many values are non numerical
# Save the combined data to a CSV file
oceandf.to_csv('OceanTemp.csv', index=False)
```

[6]:
```
oceandf = pd.read_csv('OceanTemp.csv')
oceandf.tail(10)
df = oceandf
df['temp(f)'] = pd.to_numeric(df['temp(f)'], errors='coerce')
# Create a time index
time_index = pd.date_range(start='2015-01-01 00:00:00', periods=len(df),␣
↪freq='H')

# Assign the time index to your DataFrame
df.index = time_index

# Plotting
```

```
plt.figure(figsize=(20, 6))
plt.plot(df.index, df['temp(f)'])

# Setting the number of y-ticks
y_ticks = [min(df['temp(f)']), (min(df['temp(f)']) + max(df['temp(f)'])) / 2,␣
 ↪max(df['temp(f)'])]
plt.yticks(y_ticks)

plt.xlabel('Time')
plt.ylabel('Temoperature (F)')
plt.title('Ocean Temperature')
plt.grid(True)
plt.show()
```

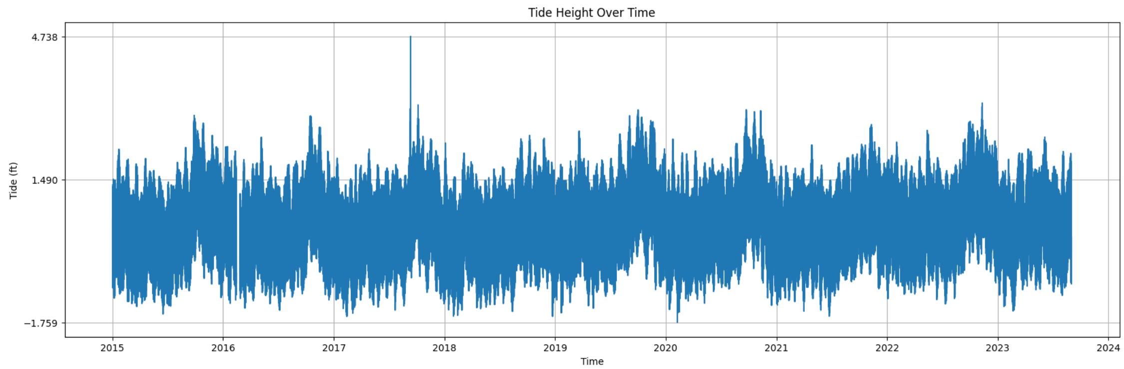


2.1.5 NOAA Tide Levels

[86]:
```
# NOAA Tide Height API
tidedf = pd.DataFrame()

for i in range(2015, 2024):  # Looping from 2015 to 2023
    start_time = f"{i}0101"
    end_time = f"{i}1231" if i != 2023 else "20230920"

    api_url = f"https://api.tidesandcurrents.noaa.gov/api/prod/datagetter?
 ↪product=hourly_height&application=NOS.COOPS.TAC.
 ↪WL&begin_date={start_time}&end_date={end_time}&datum=MSL&station=8723214&time_zone=GMT&unit

    response = requests.get(api_url)

    if response.status_code == 200:
        json_data = response.json()
        hourly_df = pd.DataFrame(json_data['data'])
```

```
        # Remove column 'f' if it exists
        if 'f' in hourly_df.columns:
            hourly_df = hourly_df.drop(columns=['f'])

        # Remove column 's' if it exists
        if 's' in hourly_df.columns:
            hourly_df = hourly_df.drop(columns=['s'])

        # Append this year's data to the master DataFrame
        tidedf = pd.concat([tidedf, hourly_df], ignore_index=True)

    else:
        print(f"Failed for year {i}: ", response.json())
#change v to tide(ft)
tidedf = tidedf.rename(columns={'v': 'tide(ft)'})
# Save the combined data to a CSV file
tidedf.to_csv('TideHeight.csv', index=False)
```

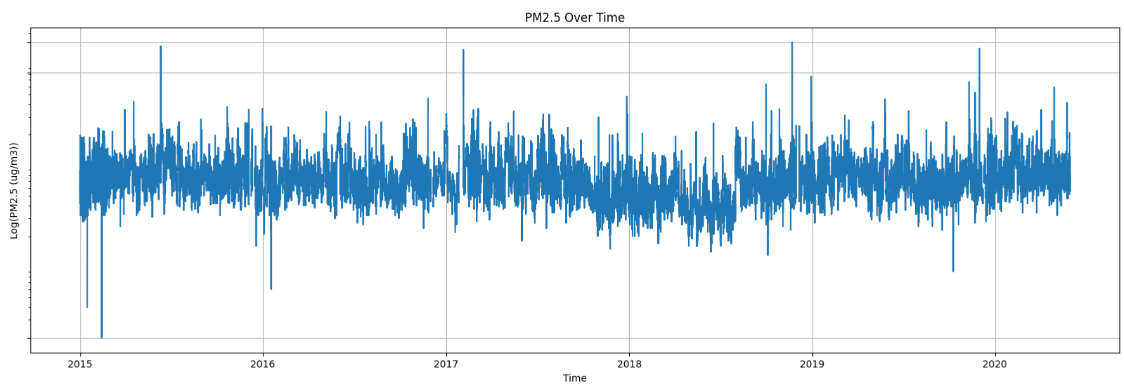
[7]:
```
#last 10 rows
tidedf = pd.read_csv('TideHeight.csv')
tidedf.tail(10)
df = tidedf
df['tide(ft)'] = pd.to_numeric(df['tide(ft)'], errors='coerce')
# Create a time index
time_index = pd.date_range(start='2015-01-01 00:00:00', periods=len(df),␣
 ↪freq='H')

# Assign the time index to your DataFrame
df.index = time_index

# Plotting
plt.figure(figsize=(20, 6))
plt.plot(df.index, df['tide(ft)'])

# Setting the number of y-ticks
y_ticks = [min(df['tide(ft)']), (min(df['tide(ft)']) + max(df['tide(ft)'])) /␣
 ↪2, max(df['tide(ft)'])]
plt.yticks(y_ticks)

plt.xlabel('Time')
plt.ylabel('Tide (ft)')
plt.title('Tide Height Over Time')
plt.grid(True)
plt.show()
```



2.1.6 PM 2.5 Data From the EPA

[101]:
```
# PM 2.5 EPA API
# https://www.epa.gov/aqs/aqs-code-list
start_time = "20150101"
end_time = "20230920"
key = ""


# NOAA Tide Height API
aqidf = pd.DataFrame()

for i in range(2015, 2024):  # Looping from 2015 to 2023
    start_time = f"{i}0101"
    end_time = f"{i}1231" if i != 2023 else "20230920"

    api_url = f"https://aqs.epa.gov/data/api/sampleData/bySite?email=marza@bu.
 ↪edu&key={key}&param=88101&bdate={start_time}&edate={end_time}&state=12&county=086&site=1016

    response = requests.get(api_url)

    if response.status_code == 200:
        json_data = response.json()
        hourly_df = pd.DataFrame(json_data['Data'])

        # Append this year's data to the master DataFrame
        aqidf = pd.concat([aqidf, hourly_df], ignore_index=True)

    else:
        print(f"Failed for year {i}: ", response.json())
# Save the combined data to a CSV file
aqidf.to_csv('PM2.5.csv', index=False)
```

```python
[27]: #last 10 rows
aqidf = pd.read_csv('PM2.5.csv')
aqidf.tail(10)
df = aqidf
df['sample_measurement'] = pd.to_numeric(df['sample_measurement'], errors='coerce')
# Create a time index
time_index = pd.date_range(start='2015-01-01 00:00:00', periods=len(df), freq='H')

# Assign the time index to your DataFrame
df.index = time_index

# Plotting
plt.figure(figsize=(20, 6))
#Log scale it
plt.yscale('log')
plt.plot(df.index, df['sample_measurement'])

# Setting the number of y-ticks
y_ticks = [min(df['sample_measurement']), (min(df['sample_measurement']) + max(df['sample_measurement'])) / 2, max(df['sample_measurement'])]
plt.yticks(y_ticks)

plt.xlabel('Time')
plt.ylabel('Log(PM2.5 (ug/m3))')
plt.title('PM2.5 Over Time')
plt.grid(True)
plt.show()
```

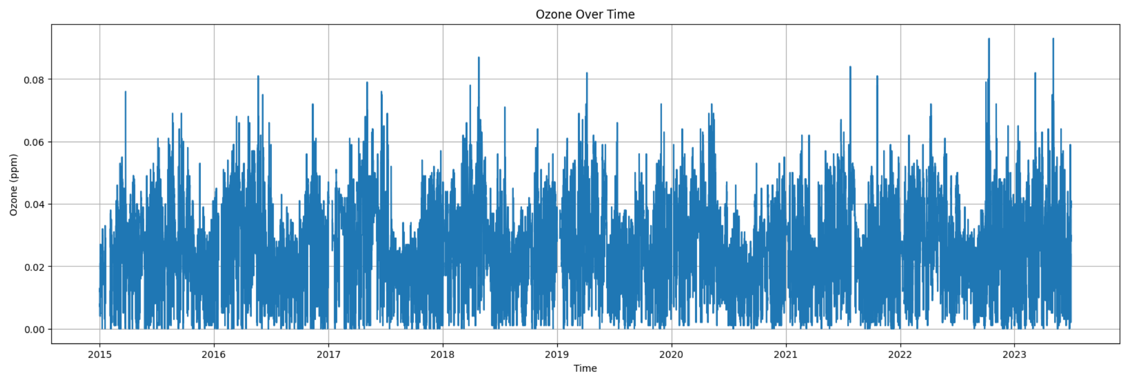


2.1.7 Ozone from EPA

[ ]:
```
# Ozone EPA API
key = ""


# NOAA Tide Height API
odf = pd.DataFrame()

for i in range(2015, 2024):  # Looping from 2015 to 2023
    start_time = f"{i}0101"
    end_time = f"{i}1231" if i != 2023 else "20230920"

    api_url = f"https://aqs.epa.gov/data/api/sampleData/bySite?email=marza@bu.
↪edu&key={key}&param=44201&bdate={start_time}&edate={end_time}&state=12&county=086&site=0029

    response = requests.get(api_url)
    if response.status_code == 200:
        json_data = response.json()
        hourly_df = pd.DataFrame(json_data['Data'])

        # Append this year's data to the master DataFrame
        odf = pd.concat([odf, hourly_df], ignore_index=True)

    else:
        print(f"Failed for year {i}: ", response.json())
# Save the combined data to a CSV file
odf.to_csv('Ozone.csv', index=False)
```

[28]:
```
#last 10 rows
odf = pd.read_csv('Ozone.csv')
odf.tail(10)
df = odf
df['sample_measurement'] = pd.to_numeric(df['sample_measurement'],␣
↪errors='coerce')
#remove nans

# Create a time index
time_index = pd.date_range(start='2015-01-01 00:00:00', periods=len(df),␣
↪freq='H')

# Assign the time index to your DataFrame
df.index = time_index

# Plotting
plt.figure(figsize=(20, 6))
```

```
plt.plot(df.index, df['sample_measurement'])

# Setting the number of y-ticks

plt.xlabel('Time')
plt.ylabel('Ozone (ppm)')
plt.title('Ozone Over Time')
plt.grid(True)
plt.show()
```



2.2 Combined Data Set

Create Time Variables

[12]:
```
#import dfs
hourly_df = pd.read_csv('MateoData.csv')
Forecastdf = pd.read_csv('ForecastData.csv')
oceandf = pd.read_csv('OceanTemp.csv')
tidedf = pd.read_csv('TideHeight.csv')
aqidf = pd.read_csv('PM2.5.csv')
odf = pd.read_csv('Ozone.csv')

#split the time in oceantemp
oceandf[['date_local', 'time_local']] = oceandf['t'].str.split(' ', expand=True)
oceandf[['year', 'month', 'day']] = oceandf['date_local'].str.split('-',␣
↪expand=True)

#split the time in tideheight
tidedf[['date_local', 'time_local']] = tidedf['t'].str.split(' ', expand=True)
tidedf[['year', 'month', 'day']] = tidedf['date_local'].str.split('-',␣
↪expand=True)

#split the time in pm2.5
```

```
aqidf[['year', 'month', 'day']] = aqidf['date_local'].str.split('-',␣
 ↪expand=True)

#split the time in ozone
odf[['year', 'month', 'day']] = odf['date_local'].str.split('-', expand=True)

#split the time in hourly
hourly_df[['date_local', 'time_local']] = hourly_df['time'].str.split('T',␣
 ↪expand=True)
hourly_df[['year', 'month', 'day']] = hourly_df['date_local'].str.split('-',␣
 ↪expand=True)
```

Combine

[13]:
```
#combine data sets into one and save into a csv
combined_df = pd.merge(hourly_df, oceandf, how='left', on=['year', 'month',␣
 ↪'day', 'time_local'])
combined_df = pd.merge(combined_df, tidedf, how='left', on=['year', 'month',␣
 ↪'day', 'time_local'])
combined_df = pd.merge(combined_df, aqidf[['year', 'month', 'day',␣
 ↪'time_local', 'sample_measurement']], how='left', on=['year', 'month',␣
 ↪'day', 'time_local'])
combined_df = combined_df.rename(columns={'sample_measurement': 'pm2.5 (ug/
 ↪m3)'})
combined_df = pd.merge(combined_df, odf[['year', 'month', 'day', 'time_local',␣
 ↪'sample_measurement']], how='left', on=['year', 'month', 'day',␣
 ↪'time_local'])
combined_df = combined_df.rename(columns={'sample_measurement': 'ozone (ppm)'})
#remove columns time, date_local_x, t_x, date_local, date_local_y
combined_df = combined_df.drop(columns=['date_local_x', 't_x', 'date_local_y',␣
 ↪'date_local', 't_y'])
#remove collon from local_time variable
combined_df['time_local'] = combined_df['time_local'].str.replace(':00', '')

#temperature_2m         relativehumidity_2m dewpoint_2m         precipitation␣
 ↪         windspeed_10m         shortwave_radiation make the nans in this␣
 ↪column 0   \
# Forecastdf.to_csv('ForecastData2.csv', index=False)
# Forecastdf = pd.read_csv('ForecastData2.csv')
Forecastdf['forecast_temp(f)'] = Forecastdf['temperature_2m'].astype(float).
 ↪fillna(0)
Forecastdf['forecast_relativehumidity_2m'] = Forecastdf['relativehumidity_2m'].
 ↪astype(float).fillna(0)
Forecastdf['forecast_dewpoint_2m'] = Forecastdf['dewpoint_2m'].astype(float).
 ↪fillna(0)
Forecastdf['forecast_precipitation'] = Forecastdf['precipitation'].
 ↪astype(float).fillna(0)
```

```
Forecastdf['forecast_windspeed_10m'] = Forecastdf['windspeed_10m'].
 ↪astype(float).fillna(0)
Forecastdf['forecast_shortwave_radiation'] = Forecastdf['shortwave_radiation'].
 ↪astype(float).fillna(0)
#remove excess columns
Forecastdf = Forecastdf.drop(columns=['temperature_2m', 'relativehumidity_2m',␣
 ↪'dewpoint_2m', 'precipitation', 'windspeed_10m', 'shortwave_radiation',␣
 ↪'Unnamed: 0'])
#save forecast df to csv
# Forecastdf.to_csv('ForecastData2.csv', index=False)
#change names of those columns to have forecast in front
#merge with forecast data
combined_df[['year', 'month', 'day', 'time_local']] = combined_df[['year',␣
 ↪'month', 'day', 'time_local']].astype('float')
Forecastdf[['year', 'month', 'day', 'time_local']] = Forecastdf[['year',␣
 ↪'month', 'day', 'time_local']].astype('float')
combined_df = pd.merge(combined_df, Forecastdf, how='left', on=['year',␣
 ↪'month', 'day', 'time_local'])
#fill nans with 0
combined_df = combined_df.fillna(0)
combined_df.to_csv('CombinedData.csv', index=False)
```

Interpolate Missing Data

[17]:
```
df = combined_df = pd.read_csv('CombinedData.csv')
#count the number of nans
combined_df['time'] = pd.to_datetime(combined_df['time'])
combined_df = combined_df.set_index('time')
combined_df.interpolate(method='time', inplace=True)
#print columns
print(combined_df.isnull().sum())
```

```
Unnamed: 0                   0
temperature_2m               0
relativehumidity_2m          0
dewpoint_2m                  0
precipitation                0
pressure_msl                 0
surface_pressure             0
cloudcover                   0
et0_fao_evapotranspiration   0
windspeed_10m                0
shortwave_radiation          0
time_local                   0
year                         0
month                        0
day                          0
temp(f)                      0
```

```
tide(ft)                        0
pm2.5 (ug/m3)                   0
ozone (ppm)                     0
forecast_temp(f)                0
forecast_relativehumidity_2m    0
forecast_dewpoint_2m            0
forecast_precipitation          0
forecast_windspeed_10m          0
forecast_shortwave_radiation    0
dtype: int64
```

[10]:
```
df = pd.read_csv('CombinedData.csv')

# Group by day, month, and year and get the maximum temperature for each group
daily_highs = df.groupby(['day', 'month', 'year'])['temperature_2m'].max().
 ↪reset_index()
daily_highs.columns = ['day', 'month', 'year', 'daily_high_temperature']
daily_highs.to_csv('DailyHighs.csv', index=False)
```

2.3 Data Exploration

2.3.1 Linear Regression Analysis of Features

[ ]:
```
# Assuming df is your DataFrame and it's already preprocessed
df = encode_features(combined_df)

numerical_cols = ['surface_pressure_5avg', 'relativehumidity_2m',␣
 ↪'dewpoint_2m', 'precipitation', 'pressure_msl','surface_pressure',␣
 ↪'cloudcover'
                        ,'et0_fao_evapotranspiration', 'windspeed_10m',␣
 ↪'shortwave_radiation', 'temp_avg','month' ,
                         'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_dewpoint_2m', 'forecast_precipitation',
                         'forecast_windspeed_10m',␣
 ↪'forecast_shortwave_radiation']
target_col = 'temperature_2m'

# Shift all forecast data up 192 rows
df['target_7_days_ahead'] = df[target_col].shift(-192)
df['forecast_temp(f)'] = df['forecast_temp(f)'].shift(-192)
df['forecast_relativehumidity_2m'] = df['forecast_relativehumidity_2m'].
 ↪shift(-192)
df['forecast_dewpoint_2m'] = df['forecast_dewpoint_2m'].shift(-192)
df['forecast_shortwave_radiation'] = df['forecast_shortwave_radiation'].
 ↪shift(-192)
df['forecast_precipitation'] = df['forecast_precipitation'].shift(-192)
df['forecast_windspeed_10m'] = df['forecast_windspeed_10m'].shift(-192)
```

```python
# Drop rows with NaN values in the specified columns
df.dropna(subset=feature_cols + ['target_7_days_ahead'], inplace=True)

# Extract feature matrix and target vector
X = df[feature_cols].values
y = df['target_7_days_ahead'].values

# Assuming you still want to slice from the 65,184th row
X = X[65184:]
y = y[65184:]

model_info = []

# Loop through each non-empty combination of features
for r in range(1, len(numerical_cols) + 1):
    for feature_subset in combinations(numerical_cols, r):

        feature_list = list(feature_subset)

        # Define X and y
        X = df[feature_list].values
        y = df[target_col].values

        # Split into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=42)

        # Initialize and fit the model with Ridge regularization
        model = Ridge(alpha=1.0)
        model.fit(X_train, y_train)

        # Make predictions
        y_pred = model.predict(X_test)

        # Calculate MAE
        mae = mean_absolute_error(y_test, y_pred)

        #calculate the r2
        r2 = model.score(X_test, y_test)

        # Store the MAE and model
        model_info.append({
            'features': feature_list,
            'mae': mae,
            'model': model,
            'loss': r2
```

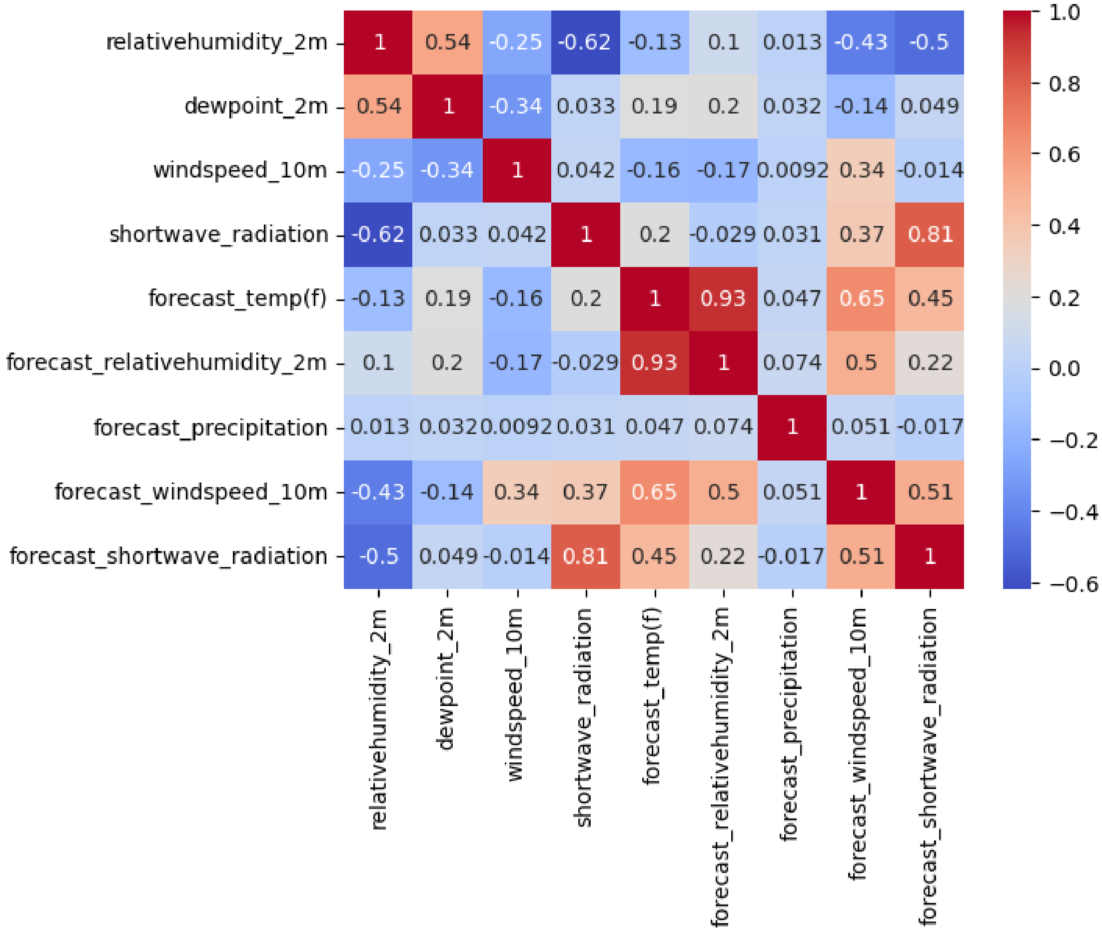
```
        })

        # Print the results
        print(f"Features: {feature_list}, MAE: {mae}", f"r2: {r2}")

# Find the model with the lowest MAE
best_model_info = min(model_info, key=lambda x: x['mae'])
print(f"The best model uses features {best_model_info['features']} with MAE␣
 ↪{best_model_info['mae']}")

def predictRegression_and_plot(month, day, year, model):

    df_inputs = input(month, day,year)
    feature_cols = best_model_info['features']
    # Prepare the input features
    X = df_inputs[feature_cols].values

    # Initialize an empty list to store predicted temperatures
    predicted_temps = []

    for i in range(24):
        # Update DataFrame to represent the current hour, if applicable

        #grab the ith row of the dataframe
        X = df_inputs.iloc[[i]]
        #grab only the features
        X = X[feature_cols].values


        # Assuming the model is already loaded and compiled
        prediction = model.predict(X)[0]  # Reshape to match the input shape␣
 ↪and take the first value
        predicted_temps.append(prediction)

    # Calculate the highest temperature for the day
    high_temp = max(predicted_temps)
    print()

    # Plotting
    plt.figure(figsize=(10, 5))
    plt.plot(range(24), predicted_temps, label='Predicted Temperatures',␣
 ↪marker='o')
    plt.axhline(y=high_temp, color='r', linestyle='-', label=f'High Temp:␣
 ↪{high_temp:.2f}')
    plt.xlabel('Hour of the Day')
    plt.ylabel('Temperature')
    plt.title('Hourly Temperature Predictions')
```

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

# Example usage:
predictRegression_and_plot("09", "29", "2023", best_model_info['model'])
```

2.3.2 Feature Correlation Map

```
[ ]: # Assuming df is your DataFrame and feature_cols is your list of feature columns
df = pd.read_csv('CombinedData.csv')
df = pd.DataFrame(df, columns=feature_cols)  # Assuming X is your feature matrix
#10 months of data
df = df[-8760:]
feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                'windspeed_10m', 'shortwave_radiation',
                'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_precipitation',
                'forecast_windspeed_10m', 'forecast_shortwave_radiation']
correlation_matrix = df[feature_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
```

```
<Axes: >
```

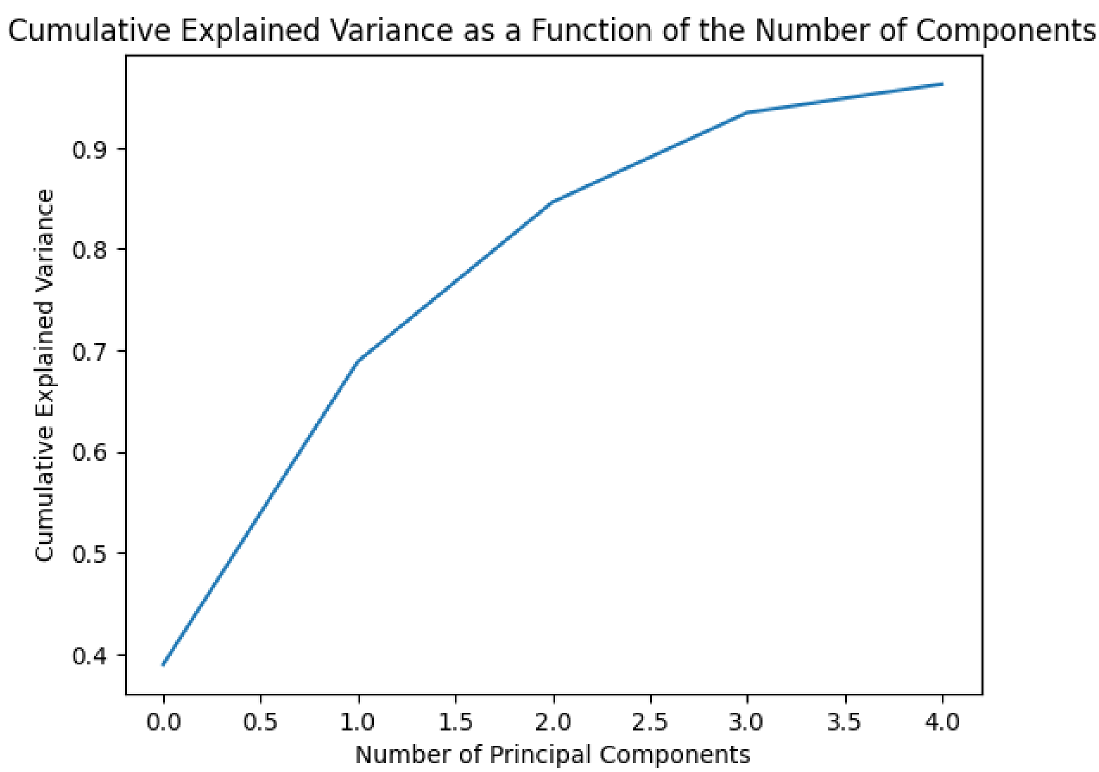


2.3.3 PCA Analysis

```
[ ]: from sklearn.decomposition import PCA
X_standardized = StandardScaler().fit_transform(df[feature_cols])

# Initialize PCA and the X vector for dimensionality reduction
pca = PCA(n_components=5)
# Fit the PCA model to your data
#only use last year of data
X = X_standardized[-8760:]
pca.fit(X)

# Get the explained variance
explained_variance = pca.explained_variance_ratio_

# Print the explained variance
print("Explained Variance: ", explained_variance)
```

```
# Sort the explained variances and their corresponding component indices
sorted_indices = np.argsort(explained_variance)[::-1]

# Print the sorted indices
print("Sorted component indices by explained variance: ", sorted_indices)

# Print the sorted explained variances
print("Sorted explained variances: ", explained_variance[sorted_indices])
cumulative_explained_variance = np.cumsum(explained_variance)

# Plot
plt.figure()
plt.plot(cumulative_explained_variance)
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Explained Variance as a Function of the Number of␣
↪Components')
plt.show()
```

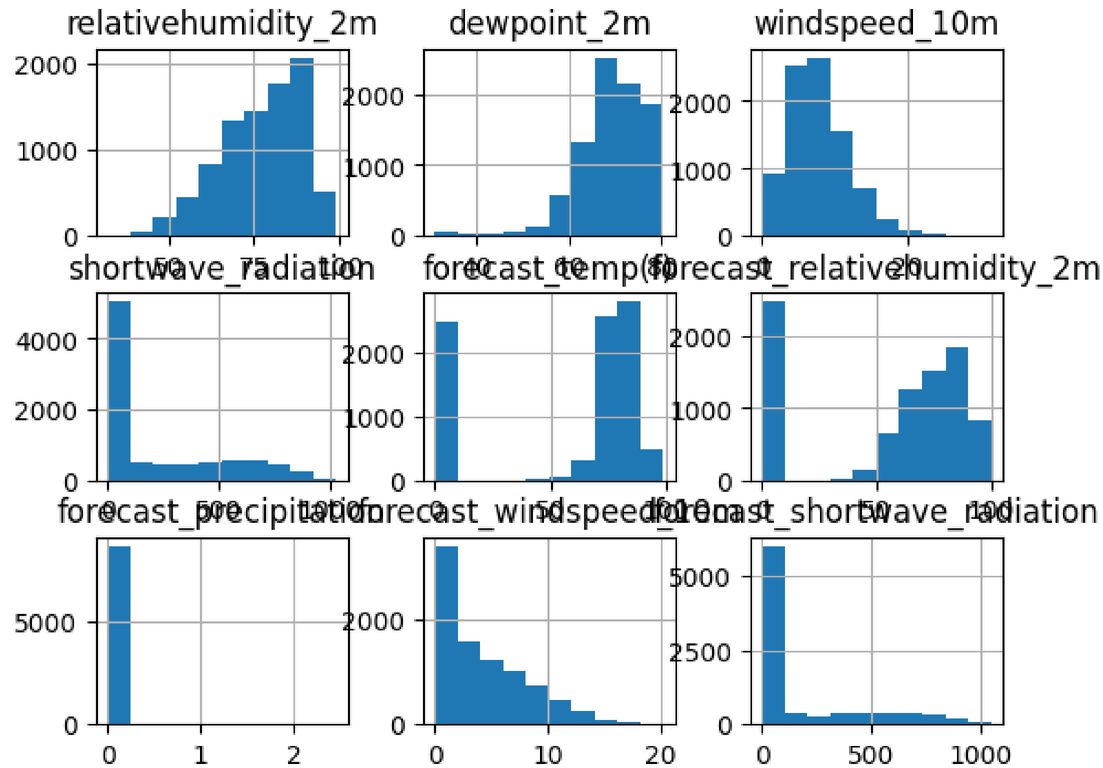
```
Explained Variance:  [0.38968215 0.29929571 0.15737064 0.08840613 0.02825785]
Sorted component indices by explained variance:  [0 1 2 3 4]
Sorted explained variances:  [0.38968215 0.29929571 0.15737064 0.08840613
0.02825785]
```



2.3.4 Feature Mean, STD, Skew, Kurtosis and more

[ ]:
```
#read csv
df = pd.read_csv("CombinedData.csv")
df = pd.DataFrame(df, columns=feature_cols)  # Assuming X is your feature matrix
#10 months of data
df = df[-8760:]
print(df.describe())

df.hist()
plt.show()

print("Skewness: ", df.skew())
print("Kurtosis: ", df.kurt())
```

```
       relativehumidity_2m  dewpoint_2m  windspeed_10m  shortwave_radiation  \
count          8760.000000  8760.000000    8760.000000          8760.000000
mean             76.907877    69.055297       7.843516           211.669064
std              12.021315     7.208439       4.200012           280.805228
min              32.000000    31.000000       0.000000             0.000000
25%              69.000000    65.500000       4.900000             0.000000
50%              78.000000    69.800000       7.200000             9.000000
75%              87.000000    74.700000      10.300000           429.000000
max              99.000000    80.400000      31.500000          1028.000000

       forecast_temp(f)  forecast_relativehumidity_2m  forecast_precipitation  \
count       8760.000000                   8760.000000             8760.000000
mean          56.773174                     53.832763                0.006198
std           36.209467                     35.523746                0.075020
min            0.000000                      0.000000                0.000000
25%            0.000000                      0.000000                0.000000
50%           75.800000                     68.000000                0.000000
75%           82.100000                     82.000000                0.000000
max           98.900000                    100.000000                2.453000

       forecast_windspeed_10m  forecast_shortwave_radiation
count             8760.000000                   8760.000000
mean                 4.112842                    167.036301
std                  3.982816                    278.954829
min                  0.000000                      0.000000
25%                  0.000000                      0.000000
50%                  3.300000                      0.000000
75%                  6.700000                    269.250000
max                 20.300000                   1049.000000
```




```
Skewness:  relativehumidity_2m             -0.590349
dewpoint_2m                     -1.524301
windspeed_10m                    0.957924
shortwave_radiation              1.003510
forecast_temp(f)                -0.873166
forecast_relativehumidity_2m    -0.681898
forecast_precipitation          19.848180
forecast_windspeed_10m           0.812134
forecast_shortwave_radiation     1.478446
dtype: float64
Kurtosis:  relativehumidity_2m              -0.253424
dewpoint_2m                       4.323818
windspeed_10m                     1.658529
shortwave_radiation              -0.438093
forecast_temp(f)                 -1.120476
forecast_relativehumidity_2m     -1.221539
forecast_precipitation          482.245025
forecast_windspeed_10m           -0.126005
forecast_shortwave_radiation      0.811738
dtype: float64
```

2.4 Models

2.4.1 Encoding

[12]:
```
def encode_features(df):
    #make float all columns
    df = df.astype(float)
    # Encode time variables using sine and cosine functions
    df['month_sin'] = np.sin(2 * np.pi * df['month'] / 12)
    df['month_cos'] = np.cos(2 * np.pi * df['month'] / 12)
    df['day_sin'] = np.sin(2 * np.pi * df['day'] / 31)
    df['day_cos'] = np.cos(2 * np.pi * df['day'] / 31)
    df['year'] = (df['year'] - df['year'].min()) / (df['year'].max() -␣
↪df['year'].min())  # Min-max scaling

    # Assume time is in 24-hour format, i.e., 0-23
    df['hour_sin'] = np.sin(2 * np.pi * df['time_local'] / 24)
    df['hour_cos'] = np.cos(2 * np.pi * df['time_local'] / 24)

    # add temperature moving average over the same hour of the day
    df['temp_avg'] = df['temperature_2m'].rolling(window=15).mean()
    df['temp_avg'] = df['temp_avg'].fillna(df['temperature_2m'])

    #surface_pressure_3avg
    df['surface_pressure_5avg'] = df['surface_pressure'].rolling(window=5).
↪mean()

    # Standardize other numerical columns
    scaler = StandardScaler()

  #add forecast data to this ['relativehumidity_2m', 'dewpoint_2m',␣
↪'precipitation', 'pressure_msl','surface_pressure', 'cloudcover',␣
↪'et0_fao_evapotranspiration', 'windspeed_10m', 'shortwave_radiation',␣
↪'temp_avg','month']
    numerical_cols =   ['surface_pressure_5avg', 'relativehumidity_2m',␣
↪'dewpoint_2m', 'precipitation', 'pressure_msl','surface_pressure',␣
↪'cloudcover'
                        ,'et0_fao_evapotranspiration', 'windspeed_10m',␣
↪'shortwave_radiation', 'temp_avg','month' ,
                         'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
↪'forecast_dewpoint_2m', 'forecast_precipitation',
                         'forecast_windspeed_10m',␣
↪'forecast_shortwave_radiation']
    df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

    return df
```

```
# Simulate your DataFrame, replace this with your real DataFrame
# df = pd.read_csv('your_dataset.csv')
```

[5]:
```
print(combined_df.iloc[70550])
```

```
Unnamed: 0                       70191.000
temperature_2m                      79.400
relativehumidity_2m                 70.000
dewpoint_2m                         69.000
precipitation                        0.000
pressure_msl                      1019.400
surface_pressure                  1019.200
cloudcover                          41.000
et0_fao_evapotranspiration           0.015
windspeed_10m                       11.500
shortwave_radiation                564.000
time_local                          15.000
year                              2023.000
month                                1.000
day                                  3.000
temp(f)                             75.000
tide(ft)                             0.289
pm2.5 (ug/m3)                        5.100
ozone (ppm)                          0.029
forecast_temp(f)                    79.400
forecast_relativehumidity_2m        69.000
forecast_dewpoint_2m                68.300
forecast_precipitation               0.000
forecast_windspeed_10m              13.900
forecast_shortwave_radiation       585.000
Name: 2023-01-03 15:00:00, dtype: float64
```

2.4.2 Second Week Model

[13]:
```
#print 65184 row of combined_df
df = combined_df.shift(-70550)
#remove empty rows
df = df.dropna()
df = encode_features(combined_df)

feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                        'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                        'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_precipitation',
                        'forecast_windspeed_10m',␣
 ↪'forecast_shortwave_radiation']
target_col = 'temperature_2m'
```

```
# Shift all forecast data up 192 rows
df['target_7_days_ahead'] = df[target_col].shift(-192)
df['forecast_temp(f)'] = df['forecast_temp(f)'].shift(-192)
df['forecast_relativehumidity_2m'] = df['forecast_relativehumidity_2m'].
↪shift(-192)
df['forecast_dewpoint_2m'] = df['forecast_dewpoint_2m'].shift(-192)
df['forecast_shortwave_radiation'] = df['forecast_shortwave_radiation'].
↪shift(-192)
df['forecast_precipitation'] = df['forecast_precipitation'].shift(-192)
df['forecast_windspeed_10m'] = df['forecast_windspeed_10m'].shift(-192)

# Drop rows with NaN values in the specified columns
df.dropna(subset=feature_cols + ['target_7_days_ahead'], inplace=True)

# Extract feature matrix and target vector
X = df[feature_cols].values
y = df['target_7_days_ahead'].values



# Custom loss function
def custom_loss(punishment_factor):
    def loss(y_true, y_pred):
        error = y_pred - y_true
        is_underestimation = K.less(y_pred, y_true)
        squared_error = K.square(error)
        return K.mean(K.switch(is_underestimation, punishment_factor *␣
↪squared_error, squared_error))
    return loss

# Create RNN model
def create_model(drop1, drop2):
    model = Sequential()
    model.add(LSTM(64, activation='tanh', input_shape=(None,␣
↪len(feature_cols)), return_sequences=True))
    model.add(Dropout(drop1))
    model.add(LSTM(32, activation='tanh'))
    model.add(Dropout(drop2))
    model.add(Dense(1))
    return model

best_mae = float('inf')
best_params = None

# Loop through different hyperparameters
for k in [5, 10]:  # Number of splits in TimeSeriesSplit
    # for drop1 in np.arange(0.1, 0.5, 0.1):  # Dropout rate for the first layer
```

```python
    #     for drop2 in np.arange(0.1, 0.5, 0.1):

    drop1 = .25
    drop2 = .25
    punish = 3

    tscv = TimeSeriesSplit(n_splits=k)

    local_best_mae = float('inf')  # Local variable to store the best MAE for␣
 ↪this configuration

    for train_index, test_index in tscv.split(X):
        # Reshape to 3D array for LSTM
        X_train, X_test = X[train_index], X[test_index]
        X_train = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
        X_test = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])

        y_train, y_test = y[train_index], y[test_index]

        model = create_model(drop1, drop2)
        model.compile(optimizer='adam', loss='mae', metrics=['mae'])
        model.fit(X_train, y_train, epochs=50, batch_size=64, verbose=0)

        loss, mae = model.evaluate(X_test, y_test, verbose=0)

        if mae < local_best_mae:
            local_best_mae = mae

    print(f"Configuration - k: {k}, drop1: {drop1}, drop2: {drop2}, MAE:␣
 ↪{local_best_mae}", "loss: ", loss)

    if local_best_mae < best_mae:
        best_mae = local_best_mae
        best_rnn_model = model
        best_params = {'k': k, 'drop1': drop1, 'drop2': drop2}

print(f"The best MAE is {best_mae} with parameters {best_params}")

# Save the best model
#best_rnn_model.save('./Model/best_rnn_model.keras')
```

```
Configuration - k: 5, drop1: 0.25, drop2: 0.25, MAE: 2.9238533973693848 loss:
28.310426712036133
Configuration - k: 10, drop1: 0.25, drop2: 0.25, MAE: 2.743997812271118 loss:
47.51902770996094
The best MAE is 2.743997812271118 with parameters {'k': 10, 'drop1': 0.25,
'drop2': 0.25}
```

2.4.3 Generate Input Parameters for Model Evaluation and Usage

[23]:
```
def input(month, day, year):

    #query for the Mateo data
    # NOAA Tide Height API


    #time
    start_time = f"{year}{month}{day}"
    start_time = pd.to_datetime(start_time) - pd.DateOffset(days=8)
    start_time = start_time.strftime("%Y%m%d")

    #ocean temp
    oceandf = pd.DataFrame()
    api_url = f"https://api.tidesandcurrents.noaa.gov/api/prod/datagetter?
↪product=water_temperature&application=NOS.COOPS.TAC.
↪PHYSOCEAN&begin_date={start_time}&end_date={start_time}&station=8723214&time_zone=GMT&units
    response = requests.get(api_url)

    if response.status_code == 200:
        json_data = response.json()
        oceandf = pd.DataFrame(json_data['data'])
        oceandf[['date_local', 'time_local']] = oceandf['t'].str.split(' ',␣
↪expand=True)
        oceandf[['year', 'month', 'day']] = oceandf['date_local'].str.
↪split('-', expand=True)
        oceandf = oceandf.drop(columns=['date_local'])
        #change name of column to tide(ft)
        oceandf = oceandf.rename(columns={'v': 'temp(f)'})
    else:
        print("Error with Ocean Temp API")
        print (response.json())


    #Mateo
    # NWS API
    # Define the start and end parameters in the correct format
    hourly_df = pd.DataFrame()
    start_time = f"{year}{month}{day}"
    #8 days ahead
    start_time = pd.to_datetime(start_time) - pd.DateOffset(days=8)
    start_time = start_time.strftime("%Y-%m-%d")


    # Build the API URL
```

```
    api_url = f"https://archive-api.open-meteo.com/v1/archive?latitude=25.
↪7934&longitude=-80.
↪29&start_date={start_time}&end_date={start_time}&hourly=temperature_2m,relativehumidity_2m,
    # Make the API request
    response = requests.get(api_url)

    if response.status_code == 200:
        json_data = response.json()
        #save data
        mateo = pd.DataFrame(json_data['hourly'])
        #split the time in hourly
        mateo[['date_local', 'time_local']] = mateo['time'].str.split('T',␣
↪expand=True)
        mateo[['year', 'month', 'day']] = mateo['date_local'].str.split('-',␣
↪expand=True)
        #remove column date_local, time
        mateo = mateo.drop(columns=['date_local', 'time'])
    else:
        print("Error with Mateo API")

    #add code for forecast data, open mateo, api_url = f"https://api.open-meteo.
↪com/v1/forecast?latitude=25.7934&longitude=-80.
↪29&hourly=temperature_2m,relativehumidity_2m,dewpoint_2m,precipitation,windspeed_10m,shortw
↪response = requests.get(api_url)
    #save data
    Forecastdf = pd.DataFrame()
    #start time is current day
    start_time = f"{year}-{month}-{day}"
    # Build the API URL
    api_url = f"https://api.open-meteo.com/v1/forecast?latitude=25.
↪7934&longitude=-80.
↪29&hourly=temperature_2m,relativehumidity_2m,dewpoint_2m,precipitation,windspeed_10m,shortw
    # Make the API request
    response = requests.get(api_url)
    if response.status_code == 200:
        json_data = response.json()
        Forecastdf = pd.DataFrame(json_data['hourly'])
        #split the time in hourly
        Forecastdf[['date_local', 'time_local']] = Forecastdf['time'].str.
↪split('T', expand=True)
        Forecastdf[['year', 'month', 'day']] = Forecastdf['date_local'].str.
↪split('-', expand=True)
        #remove column date_local, time
        Forecastdf = Forecastdf.drop(columns=['date_local', 'time'])
```

```
        Forecastdf = Forecastdf.rename(columns={'temperature_2m':␣
↪'forecast_temp(f)', 'relativehumidity_2m': 'forecast_relativehumidity_2m',␣
↪'dewpoint_2m': 'forecast_dewpoint_2m', 'precipitation':␣
↪'forecast_precipitation', 'windspeed_10m': 'forecast_windspeed_10m',␣
↪'shortwave_radiation': 'forecast_shortwave_radiation'})
    else:
        print("Error with Mateo Forecast API")


    combined_df = pd.merge(mateo, oceandf, how='left', on=['year', 'month',␣
↪'day', 'time_local'])
    combined_df = pd.merge(combined_df, Forecastdf, how='left', on=['year',␣
↪'month', 'day', 'time_local'])
    combined_df['time_local'] = combined_df['time_local'].str.replace(':00', '')
    combined_df = combined_df.drop(columns=['t', 'f'])

    #make every column float
    combined_df = combined_df.astype(float)
    #save to csv
    combined_df.to_csv('InputData2.csv', index=False)
    return encode_features(combined_df)


#input("09", "30", "2023")
```

2.4.4 Second Week Prediction

[118]:
```
def predict_and_plot_lstm(month, day, year, model):
    feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                    'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                    'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
↪'forecast_precipitation',
                    'forecast_windspeed_10m',␣
↪'forecast_shortwave_radiation']

    # Generate the input DataFrame for the specific date
    df_inputs = input(month, day, year)
    df_inputs = df_inputs.fillna(0)  # Fill missing data with 0

    # Initialize an empty list to store predicted temperatures
    predicted_temps = []

    for i in range(24):
        # Update DataFrame to represent the current hour, if applicable

        # Grab the ith row of the DataFrame
```

```
        X = df_inputs.iloc[[i]]

        # Grab only the features
        X = X[feature_cols].values

        # Reshape the input to be 3D array: (samples, time steps, features)
        X = X.reshape(1, 1, len(feature_cols))

        # Make a prediction
        prediction = model.predict(X)[0][0]
        predicted_temps.append(prediction)

    # Calculate the highest temperature for the day
    high_temp = max(predicted_temps)

    # Plotting
    plt.figure(figsize=(10, 5))
    plt.plot(range(24), predicted_temps, label='Predicted Temperatures',␣
 ↪marker='o')
    plt.axhline(y=high_temp, color='r', linestyle='-', label=f'High Temp:␣
 ↪{high_temp:.2f}')
    plt.xlabel('Hour of the Day')
    plt.ylabel('Temperature')
    plt.title('Hourly Temperature Predictions')
    plt.legend()
    plt.show()
```

[ ]:
```
predict_and_plot_lstm( "10", "30", "2023", best_rnn_model)
```

2.4.5 Evaluation: Ground Truth

[ ]:
```
def predict_and_plot_vs_ground_truth(df, model):
    ground_truth = df['temperature_2m'].values
    # model predicts 7 days ahead, reflect that in ground truth
    ground_truth = ground_truth[192:]
    #take last 10 days of data of ground truth
    ground_truth = ground_truth[-365*24:]
    df = df.tail(365*24)
    feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                    'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                    'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_precipitation',
                    'forecast_windspeed_10m',␣
 ↪'forecast_shortwave_radiation']

    df = encode_features(df)
```

```
    # Predict temperatures using the model
    predicted_temps = []
    for i in range(len(df)):
        X = df[feature_cols].iloc[[i]].values
        X = X.reshape(1, 1, len(feature_cols))
        prediction = model.predict(X)[0][0]
        predicted_temps.append(prediction)

    # Calculate the mean squared error
    #replace outliers in predicted temps
    predicted_temps = np.array(predicted_temps)
    predicted_temps[predicted_temps > 100] = 100
    #replace values less than 50
    predicted_temps[predicted_temps < 50] = 50
    # Plotting
    plt.figure(figsize=(12, 6))
    plt.plot(ground_truth, label='Ground Truth Temperatures', marker='o')
    plt.plot(predicted_temps, label='Predicted Temperatures', marker='x')
    plt.xlabel('Hour')
    plt.ylabel('Temperature')
    plt.title('Hourly Temperature: Ground Truth vs Prediction')
    plt.legend()
    plt.show()

# You'd call the function like this:
df= combined_df
predict_and_plot_vs_ground_truth(df, best_rnn_model)
```

2.4.6 Third Week Model: Bayseian LSTM

[ ]:
```
def posterior_mean_field(kernel_size, bias_size=0, dtype=None):
    n = kernel_size + bias_size
    c = np.log(np.expm1(1.))
    return tf.keras.Sequential([
        tfp.layers.VariableLayer(2 * n, dtype=dtype),
        tfp.layers.DistributionLambda(lambda t: tfp.distributions.Independent(
            tfp.distributions.Normal(loc=t[..., :n],
                                     scale=1e-5 + tf.nn.softplus(c + t[..., n:
 ↪])),
            reinterpreted_batch_ndims=1)),
    ])

def prior_trainable(kernel_size, bias_size=0, dtype=None):
    n = kernel_size + bias_size
    return tf.keras.Sequential([
        tfp.layers.VariableLayer(n, dtype=dtype),
        tfp.layers.DistributionLambda(lambda t: tfp.distributions.Independent(
```

```
            tfp.distributions.Normal(loc=t, scale=1),
            reinterpreted_batch_ndims=1)),
    ])
df = combined_df.shift(-70550)
#remove empty rows
df = df.dropna()
df = encode_features(combined_df)

feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                        'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                        'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_precipitation',
                        'forecast_windspeed_10m',␣
 ↪'forecast_shortwave_radiation','cloudcover', 'month_cos', 'day_cos']
target_col = 'temperature_2m'

# Shift all forecast data up 192 rows
df['target_7_days_ahead'] = df[target_col].shift(-192)
df['forecast_temp(f)'] = df['forecast_temp(f)'].shift(-192)
df['forecast_relativehumidity_2m'] = df['forecast_relativehumidity_2m'].
 ↪shift(-192)
df['forecast_dewpoint_2m'] = df['forecast_dewpoint_2m'].shift(-192)
df['forecast_shortwave_radiation'] = df['forecast_shortwave_radiation'].
 ↪shift(-192)
df['forecast_precipitation'] = df['forecast_precipitation'].shift(-192)
df['forecast_windspeed_10m'] = df['forecast_windspeed_10m'].shift(-192)

# Drop rows with NaN values in the specified columns
df.dropna(subset=feature_cols + ['target_7_days_ahead'], inplace=True)

# Extract feature matrix and target vector
X = df[feature_cols].values
y = df['target_7_days_ahead'].values

def sin_activation(x):
    return tf.math.sin(x)

def cos_activation(x):
    return tf.math.cos(x)

def create_bayesian_model(drop1, drop2):
    model = tf.keras.Sequential()
    model.add(Dense(64, activation='relu', input_shape=(len(feature_cols),)))
    model.add(tf.keras.layers.Dropout(drop1))
    model.add(Dense(32, activation='relu'))
    model.add(tf.keras.layers.Dropout(drop2))
```

```
    model.add(tfp.layers.DenseVariational(1, posterior_mean_field,␣
↪prior_trainable))
    return model



# Custom loss function
def custom_loss(punishment_factor):
    def loss(y_true, y_pred):
        error = y_pred - y_true
        is_underestimation = tf.less(y_pred, y_true)
        squared_error = tf.square(error)
        return tf.reduce_mean(tf.where(is_underestimation, punishment_factor *␣
↪squared_error, squared_error))
    return loss

# Initialize KFold
n_splits = 5
kf = KFold(n_splits=n_splits)

# Initialize results
mae_scores = []
best_drop=[]

# To keep track of the best model
best_bay_model = None
best_mae = float('inf')

for train_index, val_index in kf.split(X):
    for drop1 in [.1,.2,.25]:
        for drop2 in [.1,.2,.25]:
            X_train, X_val = X[train_index], X[val_index]
            y_train, y_val = y[train_index], y[val_index]

            # Create a new Bayesian model
            bayesian_model = create_bayesian_model(drop1,drop2)

            # Compile the model
            bayesian_model.compile(optimizer='adam', loss='mse',␣
↪metrics=['mae', 'mse'])

            # Fit the model
            bayesian_model.fit(X_train, y_train, epochs=50, batch_size=64,␣
↪verbose=0)

            # Evaluate the model
            loss, mae, mse = bayesian_model.evaluate(X_val, y_val, verbose=0)
```

```
            print(f"MAE for fold was: {mae}; Loss for fold was {loss}; MSE for␣
↪fold was {mse}; drop1 was {drop1}; drop2 was {drop2}")
            mae_scores.append(mae)

            # Update the best model if current model is better
            if mae < best_mae:
                best_mae = mae
                best_mse = mse
                best_drop = [drop1, drop2]
                best_bay_model = bayesian_model

# Calculate and print mean MAE
mean_mae = np.mean(mae_scores)
print(f"Mean MAE from {n_splits}-Fold CV: {mean_mae}")


# best_model now contains the best model found during k-fold cross-validation
print("Best model MAE:", best_mae, "Best model MSE:", best_mse, "Best drop1:",␣
↪best_drop[0], "Best drop2:", best_drop[1])
```

2.4.7 Prediction Week 3

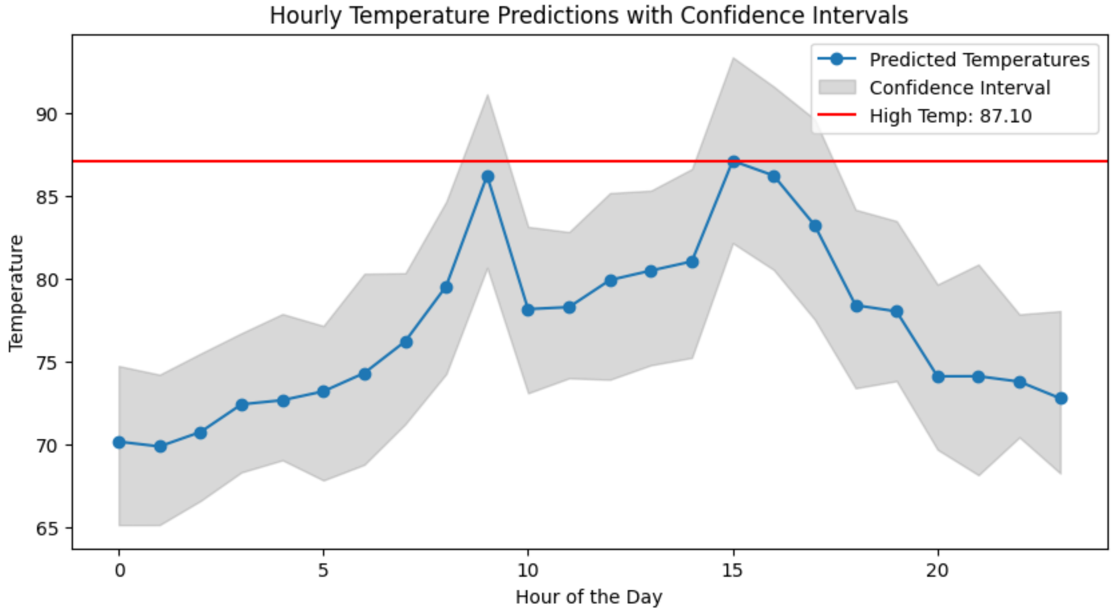
[25]:
```
def predict_and_plot_wconfid_bayesian(month, day, year, model):

    feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                    'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                    'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
↪'forecast_precipitation',
                    'forecast_windspeed_10m',␣
↪'forecast_shortwave_radiation','cloudcover', 'month_cos', 'day_cos']

    df_inputs = input(month, day, year)  # Replace with actual function
    df_inputs = df_inputs[feature_cols]
    df_inputs = df_inputs.fillna(0)

    input_shape = (5, len(feature_cols))  # Modify this as needed
    predicted_temps = []
    confidence_intervals = []
    var = []

    for i in range(24):  # Looping over 24 hours

        X = df_inputs.iloc[[i]]  # Slice DataFrame and convert to numpy array
        X = X[feature_cols].values  # Reshape array

        # Make multiple predictions and calculate confidence interval
        num_simulations = 100
```

```
        preds = [model.predict([X], verbose=0)[0][0] for _ in␣
 ↪range(num_simulations)]
        mean_pred = np.mean(preds)
        var.append(np.var(preds))

        lower_bound = np.percentile(preds, 2.5)
        upper_bound = np.percentile(preds, 97.5)

        predicted_temps.append(mean_pred)
        confidence_intervals.append((lower_bound, upper_bound))

    high_temp = max(predicted_temps)

    print(f"Variances: {var}")

    plt.figure(figsize=(10, 5))
    plt.plot(range(24), predicted_temps, label='Predicted Temperatures',␣
 ↪marker='o')

    lower_bounds, upper_bounds = zip(*confidence_intervals)
    plt.fill_between(range(24), lower_bounds, upper_bounds, color='gray',␣
 ↪alpha=0.3, label='Confidence Interval')

    plt.axhline(y=high_temp, color='r', linestyle='-', label=f'High Temp:␣
 ↪{high_temp:.2f}')
    plt.xlabel('Hour of the Day')
    plt.ylabel('Temperature')
    plt.title('Hourly Temperature Predictions with Confidence Intervals')
    plt.legend()
    plt.show()

# Usage example (make sure to replace 'best_bay_model' with the actual trained␣
 ↪model)
predict_and_plot_wconfid_bayesian("10", "05", "2023", best_bay_model)
```

```
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1050:
RuntimeWarning: invalid value encountered in divide
  updated_mean = (last_sum + new_sum) / updated_sample_count
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1055:
RuntimeWarning: invalid value encountered in divide
  T = new_sum / new_sample_count
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1075:
RuntimeWarning: invalid value encountered in divide
  new_unnormalized_variance -= correction**2 / new_sample_count
```

```
Variances: [6.7821574, 5.830461, 6.3718452, 5.2012086, 4.8586936, 5.615346,
8.01223, 6.268099, 7.443922, 8.462301, 7.089111, 5.418086, 7.4941616, 7.892386,
```

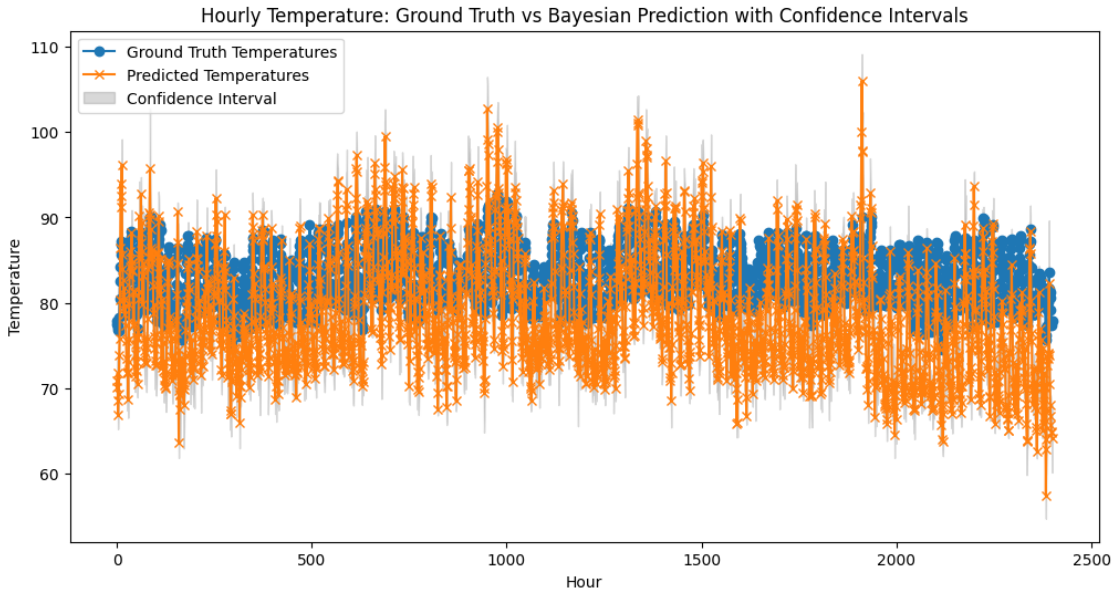
```
8.483016, 7.5383663, 8.824726, 11.036394, 8.031537, 7.032648, 7.1580715,
8.586408, 4.699601, 6.5313673]
```



2.4.8 Evaluation: Ground Truth

[40]:
```python
def predict_and_plot_vs_ground_truth_bayesian(df, model):
    # Pre-processing steps for the dataframe (similar to the first function)
    ground_truth = df['temperature_2m'].values
    # model predicts 7 days ahead, reflect that in ground truth
    ground_truth = ground_truth[192:]
    #take last 10 days of data of ground truth
    ground_truth = ground_truth[-100*24:]
    df = df.tail(100*24)
    df = df.dropna()
    df = encode_features(df)

    feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                    'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                    'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
 ↪'forecast_precipitation',
                    'forecast_windspeed_10m', 'forecast_shortwave_radiation',
                    'cloudcover', 'month_cos', 'day_cos']

    # Assuming the actual temperature column in your dataset is named␣
 ↪'temperature_2m'

    predicted_temps = []
```

```
    confidence_intervals = []

    for i in range(len(df)):
        X = df[feature_cols].iloc[[i]].values

        # Make multiple predictions and calculate confidence interval
        num_simulations = 3
        preds = [model.predict([X], verbose=0)[0][0] for _ in␣
 ↪range(num_simulations)]
        mean_pred = np.mean(preds)
        lower_bound = np.percentile(preds, 2.5)
        upper_bound = np.percentile(preds, 97.5)

        predicted_temps.append(mean_pred)
        confidence_intervals.append((lower_bound, upper_bound))



    # Plotting
    plt.figure(figsize=(12, 6))
    plt.plot(ground_truth, label='Ground Truth Temperatures', marker='o')
    plt.plot(predicted_temps, label='Predicted Temperatures', marker='x')

    lower_bounds, upper_bounds = zip(*confidence_intervals)
    plt.fill_between(range(len(df)), lower_bounds, upper_bounds, color='gray',␣
 ↪alpha=0.3, label='Confidence Interval')

    plt.xlabel('Hour')
    plt.ylabel('Temperature')
    plt.title('Hourly Temperature: Ground Truth vs Bayesian Prediction with␣
 ↪Confidence Intervals')
    plt.legend()
    plt.show()

# Usage example
df = combined_df
predict_and_plot_vs_ground_truth_bayesian(df, best_bay_model)
```



2.5 Automation

2.5.1 Automated Model Data Retrieval for Automated Trading

[ ]:
```
def maxTemps(month, day, year, model):
    feature_cols = ['relativehumidity_2m', 'dewpoint_2m',
                    'windspeed_10m', 'shortwave_radiation', 'temp_avg',
                    'forecast_temp(f)', 'forecast_relativehumidity_2m',␣
↪'forecast_precipitation',
                    'forecast_windspeed_10m',␣
↪'forecast_shortwave_radiation','cloudcover', 'month_cos', 'day_cos']

    df_inputs = input(month, day, year)  # Replace with actual function
    df_inputs = df_inputs[feature_cols]
    df_inputs = df_inputs.fillna(0)

    input_shape = (1, len(feature_cols))  # Modify this as needed

    max_temps = []

    for sim in range(100):  # 100 Bayesian simulations
        predicted_temps = []

        for i in range(24):  # Looping over 24 hours
            X = df_inputs.iloc[[i]]  # Slice DataFrame and convert to numpy␣
↪array
            X = X[feature_cols].values  # Reshape array
```

```
            pred = model.predict([X], verbose=0)[0][0]
            predicted_temps.append(pred)

        max_temps.append(max(predicted_temps))

    return max_temps

def interval(temp_interval, max_temps):
    lower, upper = temp_interval
    #round max_temps
    max_temps = [round(temp) for temp in max_temps]
    count = sum(lower <= temp <= upper for temp in max_temps)
    probability = count / len(max_temps)
    return probability
```

2.5.2 Kalshi API

[7]:
```
def login():
    url = 'https://demo-api.kalshi.co/trade-api/v2/login'
    payload = {
        "email": "marza@bu.edu",
        "password": ""
    }
    headers = {
        "accept": "application/json",
        "content-type": "application/json"
    }
    response = requests.post(url, json=payload, headers=headers)
    if response.status_code == 200:
        print("Login Successful")
        return response.json()
    else:
        print("Login Failed")
        print(response.json())
        return None

def placeOrder(count):
    credentials = login()

    url = "https://demo-api.kalshi.co/trade-api/v2/portfolio/orders"

    payload = {
        "action": "buy",
        "client_order_id": f"{credentials['member_id']}",
        "count": f"{count}",
        "expiration_ts": 300,
        "side": "yes",
```

```
        "type": "market",
        "ticker": "highmia-23oct02",
        "Authorization": f"{credentials['token']}"
    }
    headers = {
        "accept": "application/json",
        "content-type": "application/json"
    }

    response = requests.post(url, json=payload, headers=headers)
    if response.status_code == 200:
        print("Order Placed")
        return response.json()
    else:
        print("Order Failed")
        print(response.json())
        return None
```

[23]:

```
def placeOrder(month, day, cnt):
    guess = round(predcit_ffn(month, day, "2023", best_model))
    # print the guess for the day ... is ...
    print("The guess for the day " + f"{month}-{day}" " is: " + str(guess))

    config = kalshi_python.Configuration()
    config.host = 'https://demo-api.kalshi.co/trade-api/v2'
    kalshi_api = kalshi_python.ApiInstance(
        email='marza@bu.edu',
        password='',
        configuration=config,
    )

    exchangeStatus = kalshi_api.get_exchange_status()
    if exchangeStatus.trading_active:
        month = (calendar.month_abbr[int(month)]).upper()
        eventTicker = f"HIGHMIA-23{month}{day}"
        print ("Event ticker: " + eventTicker)
        eventResponse = kalshi_api.get_event(eventTicker)
        eventResponse = eventResponse.to_dict()
        ifstart = True
        marketTicker = ''
        for x in eventResponse['markets']:
            # Split the ticker by '-' and take the last part
            x = x['ticker']
            value = x.split('-')[-1]
            op = value[0]
            value = float(value[1:])
            if(ifstart and op == 'T'):
```

```
                if(guess <= round(value - 1)):
                    marketTicker = x
                    break
                ifstart = False
            elif(op == 'B'):
                if(guess <= round(value + .5) and guess >= round(value - .5)):
                    marketTicker = x
                    break
            else:
                if(guess >= round(value + 1)):
                    marketTicker = x
                    break
        if(marketTicker != ''):
            print(marketTicker)
            orderUuid = str(uuid.uuid4())
            orderResponse = kalshi_api.create_order(CreateOrderRequest(
                ticker=marketTicker,
                action='buy',
                type='market',
                count= cnt,
                buy_max_cost= 65,
                expiration_ts = int(time.time()) + 300,
                client_order_id=orderUuid,
                side='yes',
            ))
            orderResponse = orderResponse.to_dict()
            status = orderResponse['order']['status']
            print('\nOrder submitted: ' + status)
        else:
            print("No market found")
    else:
        print("Exchange is closed")


def placeOrderNo(month, day, cnt):
    guess = round(predcit_ffn(month, day, "2023", best_model))
    # print the guess for the day ... is ...
    print("The guess for the day " + f"{month}-{day}" " is: " + str(guess))

    config = kalshi_python.Configuration()
    config.host = 'https://demo-api.kalshi.co/trade-api/v2'
    kalshi_api = kalshi_python.ApiInstance(
        email='marza@bu.edu',
        password='',
        configuration=config,
    )
```

```
exchangeStatus = kalshi_api.get_exchange_status()
if exchangeStatus.trading_active:
    month = (calendar.month_abbr[int(month)]).upper()
    eventTicker = f"HIGHMIA-23{month}{day}"
    print ("Event ticker: " + eventTicker)
    eventResponse = kalshi_api.get_event(eventTicker)
    eventResponse = eventResponse.to_dict()
    ifstart = True
    marketTicker = []
    print(eventResponse['markets'])
    for x in eventResponse['markets']:
        # Split the ticker by '-' and take the last part
        x = x['ticker']
        value = x.split('-')[-1]
        op = value[0]
        value = float(value[1:])
        if(ifstart and op == 'T'):
            if(guess > round(value - 1)):
                marketTicker.append(x)
            ifstart = False
        elif(op == 'B'):
            if(guess > round(value + .5) or guess < round(value - .5)):
                marketTicker.append(x)
        else:
            if(guess < round(value + 1)):
                marketTicker.append(x)
    print(marketTicker)
    #current time in seconds
    for x in marketTicker:
        print(x)
        orderUuid = str(uuid.uuid4())
        orderResponse = kalshi_api.create_order(CreateOrderRequest(
            ticker=x,
            action='buy',
            type='limit',
            no_price= 65,
            expiration_ts = int(time.time()) + 300,
            count= cnt,
            client_order_id=orderUuid,
            side='no',
        ))
        orderResponse = orderResponse.to_dict()
        status = orderResponse['order']['status']
        print('\nOrder submitted: ' + status)
        print(orderResponse)
else:
    print("Exchange is closed")
```

```
def placeOrderAll(month, day, year, cnt, model):
    max_temps= maxTemps(month, day, year, model)

    config = kalshi_python.Configuration()
    config.host = 'https://demo-api.kalshi.co/trade-api/v2'
    kalshi_api = kalshi_python.ApiInstance(
        email='marza@bu.edu',
        password='',
        configuration=config,
    )

    exchangeStatus = kalshi_api.get_exchange_status()
    if exchangeStatus.trading_active:
        month = (calendar.month_abbr[int(month)]).upper()
        eventTicker = f"HIGHMIA-23{month}{day}"
        print ("Event ticker: " + eventTicker)
        eventResponse = kalshi_api.get_event(eventTicker)
        eventResponse = eventResponse.to_dict()
        ifstart = True
        yes = 0
        no = 0
        print(eventResponse['markets'])
        for x in eventResponse['markets']:
            # Split the ticker by '-' and take the last part
            x = x['ticker']
            value = x.split('-')[-1]
            op = value[0]
            value = float(value[1:])
            if(ifstart and op == 'T'):
                p = interval((-30, value - 1), max_temps)
                yes = round(p*100)-5
                no = round((1-p)*100)-5
                ifstart = False
            elif(op == 'B'):
                p = interval((value - .5, value + .5), max_temps)
                yes = round(p*100)-5
                no = round((1-p)*100)-5
            else:
                p = interval((value + 1, 130), max_temps)
                yes = round(p*100)-5
                no = round((1-p)*100)-5
            #send yes trade
            print(x)
            print(yes)
            print(no)
            if(yes>0):
```

```python
                orderUuid = str(uuid.uuid4())
                orderResponse = kalshi_api.create_order(CreateOrderRequest(
                    ticker=x,
                    action='buy',
                    type='limit',
                    yes_price= yes,
                    expiration_ts = int(time.time()) + (3600*20),
                    count= cnt,
                    client_order_id=orderUuid,
                    side='yes',
                ))
                orderResponse = orderResponse.to_dict()
                status = orderResponse['order']['status']
                print('\nOrder submitted: ' + status)
                print(orderResponse)
            #send no trade
            if(no>0):
                orderUuid = str(uuid.uuid4())
                orderResponse = kalshi_api.create_order(CreateOrderRequest(
                    ticker=x,
                    action='buy',
                    type='limit',
                    no_price= no,
                    expiration_ts = int(time.time()) + (3600*20),
                    count= cnt,
                    client_order_id=orderUuid,
                    side='no',

                ))
                orderResponse = orderResponse.to_dict()
                status = orderResponse['order']['status']
                print('\nOrder submitted: ' + status)
                print(orderResponse)

    else:
        print("Exchange is closed")
```

[26]:

```python
placeOrderAll("10", "11", "2023", 100, best_bay_model)
```

```
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1050:
RuntimeWarning: invalid value encountered in divide
  updated_mean = (last_sum + new_sum) / updated_sample_count
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1055:
```

```
RuntimeWarning: invalid value encountered in divide
  T = new_sum / new_sample_count
/opt/homebrew/lib/python3.11/site-packages/sklearn/utils/extmath.py:1075:
RuntimeWarning: invalid value encountered in divide
  new_unnormalized_variance -= correction**2 / new_sample_count
```

Event ticker: HIGHMIA-23OCT11

[{'can_close_early': True, 'cap_strike': 84, 'category': '', 'close_time':
'2023-10-12T03:59:00Z', 'custom_strike': None, 'event_ticker': '',
'expiration_time': '2023-10-18T14:00:00Z', 'expiration_value': '',
'floor_strike': None, 'last_price': 0, 'liquidity': 0, 'no_ask': 0, 'no_bid': 0,
'open_interest': 0, 'open_time': '2023-10-10T14:00:00Z', 'previous_price': 0,
'previous_yes_ask': 6, 'previous_yes_bid': 0, 'result': '', 'risk_limit_cents':
2500000, 'status': 'active', 'strike_type': 'less', 'subtitle': '83° or below',
'ticker': 'HIGHMIA-23OCT11-T84', 'title': '', 'volume': 0, 'volume_24h': 0,
'yes_ask': 100, 'yes_bid': 0}, {'can_close_early': True, 'cap_strike': 85,
'category': '', 'close_time': '2023-10-12T03:59:00Z', 'custom_strike': None,
'event_ticker': '', 'expiration_time': '2023-10-18T14:00:00Z',
'expiration_value': '', 'floor_strike': 84, 'last_price': 0, 'liquidity': 0,
'no_ask': 0, 'no_bid': 0, 'open_interest': 0, 'open_time':
'2023-10-10T14:00:00Z', 'previous_price': 0, 'previous_yes_ask': 11,
'previous_yes_bid': 1, 'result': '', 'risk_limit_cents': 2500000, 'status':
'active', 'strike_type': 'between', 'subtitle': '84° to 85°', 'ticker':
'HIGHMIA-23OCT11-B84.5', 'title': '', 'volume': 0, 'volume_24h': 0, 'yes_ask':
100, 'yes_bid': 0}, {'can_close_early': True, 'cap_strike': 87, 'category': '',
'close_time': '2023-10-12T03:59:00Z', 'custom_strike': None, 'event_ticker': '',
'expiration_time': '2023-10-18T14:00:00Z', 'expiration_value': '',
'floor_strike': 86, 'last_price': 0, 'liquidity': 0, 'no_ask': 0, 'no_bid': 0,
'open_interest': 0, 'open_time': '2023-10-10T14:00:00Z', 'previous_price': 0,
'previous_yes_ask': 21, 'previous_yes_bid': 11, 'result': '',
'risk_limit_cents': 2500000, 'status': 'active', 'strike_type': 'between',
'subtitle': '86° to 87°', 'ticker': 'HIGHMIA-23OCT11-B86.5', 'title': '',
'volume': 0, 'volume_24h': 0, 'yes_ask': 100, 'yes_bid': 0}, {'can_close_early':
True, 'cap_strike': 89, 'category': '', 'close_time': '2023-10-12T03:59:00Z',
'custom_strike': None, 'event_ticker': '', 'expiration_time':
'2023-10-18T14:00:00Z', 'expiration_value': '', 'floor_strike': 88,
'last_price': 36, 'liquidity': 0, 'no_ask': 0, 'no_bid': 0, 'open_interest':
100, 'open_time': '2023-10-10T14:00:00Z', 'previous_price': 36,
'previous_yes_ask': 100, 'previous_yes_bid': 26, 'result': '',
'risk_limit_cents': 2500000, 'status': 'active', 'strike_type': 'between',
'subtitle': '88° to 89°', 'ticker': 'HIGHMIA-23OCT11-B88.5', 'title': '',
'volume': 100, 'volume_24h': 100, 'yes_ask': 100, 'yes_bid': 0},
{'can_close_early': True, 'cap_strike': 91, 'category': '', 'close_time':
'2023-10-12T03:59:00Z', 'custom_strike': None, 'event_ticker': '',
'expiration_time': '2023-10-18T14:00:00Z', 'expiration_value': '',
'floor_strike': 90, 'last_price': 0, 'liquidity': 0, 'no_ask': 0, 'no_bid': 0,
'open_interest': 0, 'open_time': '2023-10-10T14:00:00Z', 'previous_price': 0,
'previous_yes_ask': 33, 'previous_yes_bid': 23, 'result': '',

'risk_limit_cents': 2500000, 'status': 'active', 'strike_type': 'between',
'subtitle': '90° to 91°', 'ticker': 'HIGHMIA-23OCT11-B90.5', 'title': '',
'volume': 0, 'volume_24h': 0, 'yes_ask': 100, 'yes_bid': 0}, {'can_close_early':
True, 'cap_strike': None, 'category': '', 'close_time': '2023-10-12T03:59:00Z',
'custom_strike': None, 'event_ticker': '', 'expiration_time':
'2023-10-18T14:00:00Z', 'expiration_value': '', 'floor_strike': 91,
'last_price': 0, 'liquidity': 0, 'no_ask': 0, 'no_bid': 0, 'open_interest': 0,
'open_time': '2023-10-10T14:00:00Z', 'previous_price': 0, 'previous_yes_ask':
23, 'previous_yes_bid': 13, 'result': '', 'risk_limit_cents': 2500000, 'status':
'active', 'strike_type': 'greater', 'subtitle': '92° or above', 'ticker':
'HIGHMIA-23OCT11-T91', 'title': '', 'volume': 0, 'volume_24h': 0, 'yes_ask':
100, 'yes_bid': 0}]
HIGHMIA-23OCT11-T84
-5
95

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'd743cf0c-5f93-413f-bb52-ae1df7dbf17c', 'created_time':
'2023-10-11T13:49:07.327551Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 95, 'order_id': '99d982c3-0038-4d59-a406-0f81d8d9fd9c', 'side':
'no', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-T84', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 5}}
HIGHMIA-23OCT11-B84.5
-3
93

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'3d2461c7-69b8-4046-a5f3-5de0d146c548', 'created_time':
'2023-10-11T13:49:07.503185Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 93, 'order_id': '641b1b56-e145-4ba6-80af-71a290848aff', 'side':
'no', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B84.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 7}}
HIGHMIA-23OCT11-B86.5
5
85

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'84cd8d78-3ead-47a3-a543-176d2707c741', 'created_time':
'2023-10-11T13:49:07.67583Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 95, 'order_id': '265776d4-5410-4ed6-9819-3c6ee58c335d', 'side':
'yes', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B86.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 5}}

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':

'b7e02606-88d2-4abd-9384-451d21916b94', 'created_time':
'2023-10-11T13:49:07.836443Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 85, 'order_id': '32feb10e-b6c1-47a5-a732-54e3f7f97fff', 'side':
'no', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B86.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 15}}
HIGHMIA-23OCT11-B88.5
18
72

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'8815651e-db5a-49f9-b4a7-e6d6b0b7cda5', 'created_time':
'2023-10-11T13:49:08.009459Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 82, 'order_id': '3589de43-f4b4-4d45-b1f7-ada0b4d2a5ba', 'side':
'yes', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B88.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 18}}

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'58bafcae-e50b-4d03-b48b-8f39f299de42', 'created_time':
'2023-10-11T13:49:08.180973Z', 'expiration_time': '2023-10-12T09:49:07Z',
'no_price': 72, 'order_id': 'ae5357b2-60a5-49ae-b5e8-dd3578ff2593', 'side':
'no', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B88.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 28}}
HIGHMIA-23OCT11-B90.5
28
62

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id':
'ecc6acae-158e-4f64-a666-e84e58be4677', 'created_time':
'2023-10-11T13:49:08.346524Z', 'expiration_time': '2023-10-12T09:49:08Z',
'no_price': 72, 'order_id': '69f0a918-e1e9-41e6-9dd6-e8caf8cf0f64', 'side':
'yes', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-B90.5', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 28}}

Order submitted: resting
{'order': {'action': 'buy', 'client_order_id': '3cd4b855-f89a-47ad-
bc4b-142d992f284f', 'created_time': '2023-10-11T13:49:08.506689Z',
'expiration_time': '2023-10-12T09:49:08Z', 'no_price': 62, 'order_id':
'ce40af81-52c2-408d-b32e-5e08c7abe610', 'side': 'no', 'status': 'resting',
'ticker': 'HIGHMIA-23OCT11-B90.5', 'type': 'limit', 'user_id':
'6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 38}}
HIGHMIA-23OCT11-T91
27
63

Order submitted: resting

{'order': {'action': 'buy', 'client_order_id':
'145e17bd-85c6-4e6b-80fc-a7c732c92278', 'created_time':
'2023-10-11T13:49:08.667436Z', 'expiration_time': '2023-10-12T09:49:08Z',
'no_price': 73, 'order_id': 'b57cc3a8-ba59-4f2d-abc6-3052d22a5e7a', 'side':
'yes', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-T91', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 27}}

Order submitted: resting

{'order': {'action': 'buy', 'client_order_id':
'02f24933-99b1-499d-858b-4ed88459704d', 'created_time':
'2023-10-11T13:49:08.831608Z', 'expiration_time': '2023-10-12T09:49:08Z',
'no_price': 63, 'order_id': 'a05dc09a-4a7a-4ad0-b2d9-81d780be796d', 'side':
'no', 'status': 'resting', 'ticker': 'HIGHMIA-23OCT11-T91', 'type': 'limit',
'user_id': '6a3dc078-e141-43cb-8b4c-67af06a771e2', 'yes_price': 37}}

2.6 Imports

[2]:
```python
## Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import requests
import json
from sklearn.model_selection import TimeSeriesSplit
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM
#from keras.models import load_model
from tensorflow.keras import backend as K
from itertools import combinations
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
#ridge
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
import kalshi_python
from kalshi_python.models import *
import uuid
import calendar
import time
import tensorflow as tf
import tensorflow_probability as tfp
from sklearn.model_selection import KFold
```