rf

December 4, 2024

[1]:

```
# import necessary libraries
import pandas as pd
```

[2]:

```
data = pd.read_csv('df_merged_weekly.csv', index_col=0)
data['dt'] = pd.to_datetime(data['dt'])
data.head()
```

[2]:

```
     week         dt  Cases    temp  feels_like  pressure  humidity  \
0  2022-1 2022-01-01    7.0  298.38      299.64    1013.0      87.0
1  2022-2 2022-01-08    1.0  302.23      308.88    1011.0      68.0
2  2022-3 2022-01-15    2.0  300.74      304.09    1013.0      58.0
3  2022-4 2022-01-22    3.0  302.42      309.89    1010.0      63.0
4  2022-5 2022-01-29    3.0  303.37      308.69    1010.0      64.0

   precipitation
0           3.14
1           0.00
2           0.00
3           0.00
4           0.42
```

[3]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 140 entries, 0 to 139
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   week           140 non-null    object
 1   dt             140 non-null    datetime64[ns]
 2   Cases          140 non-null    float64
 3   temp           140 non-null    float64
 4   feels_like     140 non-null    float64
 5   pressure       140 non-null    float64
 6   humidity       140 non-null    float64
 7   precipitation  140 non-null    float64
dtypes: datetime64[ns](1), float64(6), object(1)
memory usage: 9.8+ KB
```

1 Columns

column	description	type
week	week corresponding to the specific year	datetime
dt	specific date	datetime
Cases	Dengue Cases	integer
temp	Average temperature in the given week	numeric
feels_like	Average feels_life in the given week	numeric
pressure	Average pressure in the given week	numeric
humidity	Average humidity in the given week	numeric
precipitation	Total precipitation in the given week	numeric

1.1 Training data

Data used to be trained range from 2022 to 2023

1.2 Testing data

Data used to be tested is 2024 (also used for training)

[4]:

```
# Training the rf model
# defining a function for general looping of n-week aheads
from sklearn.ensemble import RandomForestRegressor
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error

def train_rf(data, features, target, date_col, n_ahead):
    # Select relevant columns
    rel_col = features + [target] + [date_col]
    data = data[rel_col]

    # Getting the first and last index for the year 2024
    first_2024 = data[data['dt'].dt.year == 2024].index[0]  # First index of␣
 ↪2024
    last_2024 = data[data['dt'].dt.year == 2024].index[-1]  # Last index of 2024

    first_2024subn = first_2024 - n_ahead # Subtract n_ahead weeks from first␣
 ↪date of 2024
    last_2024subn = last_2024 - n_ahead  # Subtract n_ahead weeks from last␣
 ↪date of 2024

    # Define lags
    env_lags = [2]   #2-week lag for environment features
    cases_lag = range(1, 12)  # 1 to 11 week lags for target variable

    # Create lagged features for environment and target variables
    for lag in env_lags:
        for feature in features:
            data[f'{feature}_lag_{lag}'] = data[feature].shift(lag)

    for lag in cases_lag:
        data[f'{target}_lag_{lag}'] = data[target].shift(lag)

    # Remove any rows with missing values due to lagging
    data = data.dropna()

    # Initialize list for storing predictions
    predict_data = []

    # Loop through data to get n-week ahead prediction
    index_begin = first_2024subn
    index_end = last_2024subn

    while index_begin <= index_end:
        rf = RandomForestRegressor(n_estimators=300)  # RandomForestRegressor␣
↪with 100 estimators (can be tuned)

        # Split data into training and testing sets
        train_data = data[data.index <= index_begin]  # All rows up to␣
↪index_begin
        test_data = data.iloc[data.index.get_loc(index_begin):data.index.
↪get_loc(index_begin) + n_ahead]  # Next n_ahead rows

        X_train = train_data.drop(columns=[target, date_col])  # Drop target␣
↪and date column for training data
        y_train = train_data[target]
        X_test = test_data.drop(columns=[target, date_col])  # Drop target and␣
↪date column for test data
        y_test = test_data[target]

        # Fit the RandomForest model
        rf.fit(X_train, y_train)

        # Get the last prediction (n-week ahead prediction)
        predict_data.append(rf.predict(X_test)[-1])

        # Increment the index to the next week
        index_begin += 1
    MAE = mean_absolute_error(predict_data, data[data['dt'].dt.year ==␣
↪2024]['Cases'])
```

```
    return predict_data, MAE
```

[5]:

```
# Perform Initial Testing
target="Cases"
features=["temp","humidity","precipitation"]
date = 'dt'
prediction_1_week, MAE_1_week = train_rf(data, features, target, date, 1)
prediction_4_week, MAE_4_week = train_rf(data, features, target, date, 4)
prediction_12_week, MAE_12_week = train_rf(data, features, target, date, 12)
```

[6]:

```
print(f'The Mean Absolute Error of the 1-Week Ahead Model is {MAE_1_week}')
print(f'The Mean Absolute Error of the 4-Week Ahead Model is {MAE_4_week}')
print(f'The Mean Absolute Error of the 12-Week Ahead Model is {MAE_12_week}')
```

```
The Mean Absolute Error of the 1-Week Ahead Model is 13.745370370370372
The Mean Absolute Error of the 4-Week Ahead Model is 21.459814814814813
The Mean Absolute Error of the 12-Week Ahead Model is 22.671759259259257
```

[7]:

```
prediction_1_week[:5]
```

[7]:

```
[19.623333333333335,
 19.143333333333334,
 16.42,
 19.273333333333333,
 19.463333333333335]
```

[8]:

```
prediction_4_week[:5]
```

[8]:

```
[29.08, 26.673333333333332, 13.353333333333333, 12.546666666666667, 21.09]
```

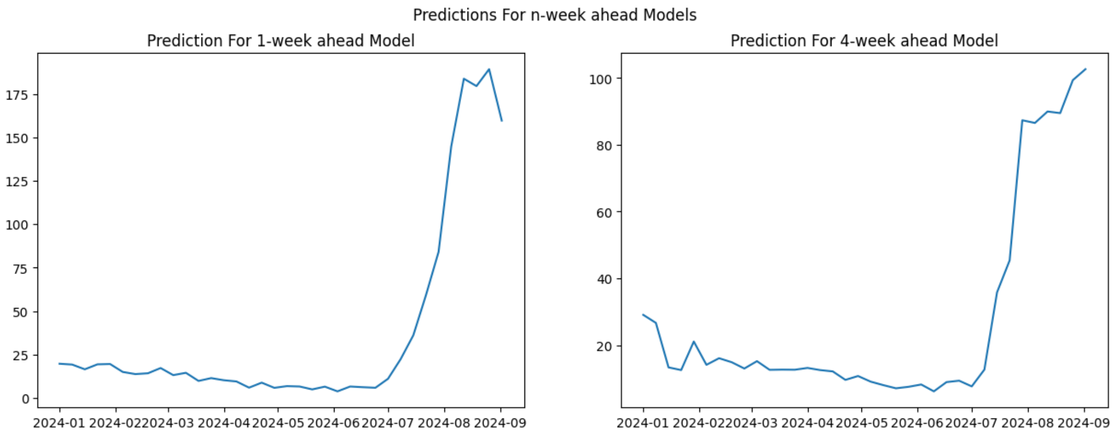
2 Visualization

[9]:

```
import matplotlib.pyplot as plt
first_2024 = int((data['dt'].dt.year==2024).idxmax())
last_2024 = int(data.loc[data['dt'].dt.year == 2024].index[-1])
date = data.loc[first_2024:last_2024]['dt']
```

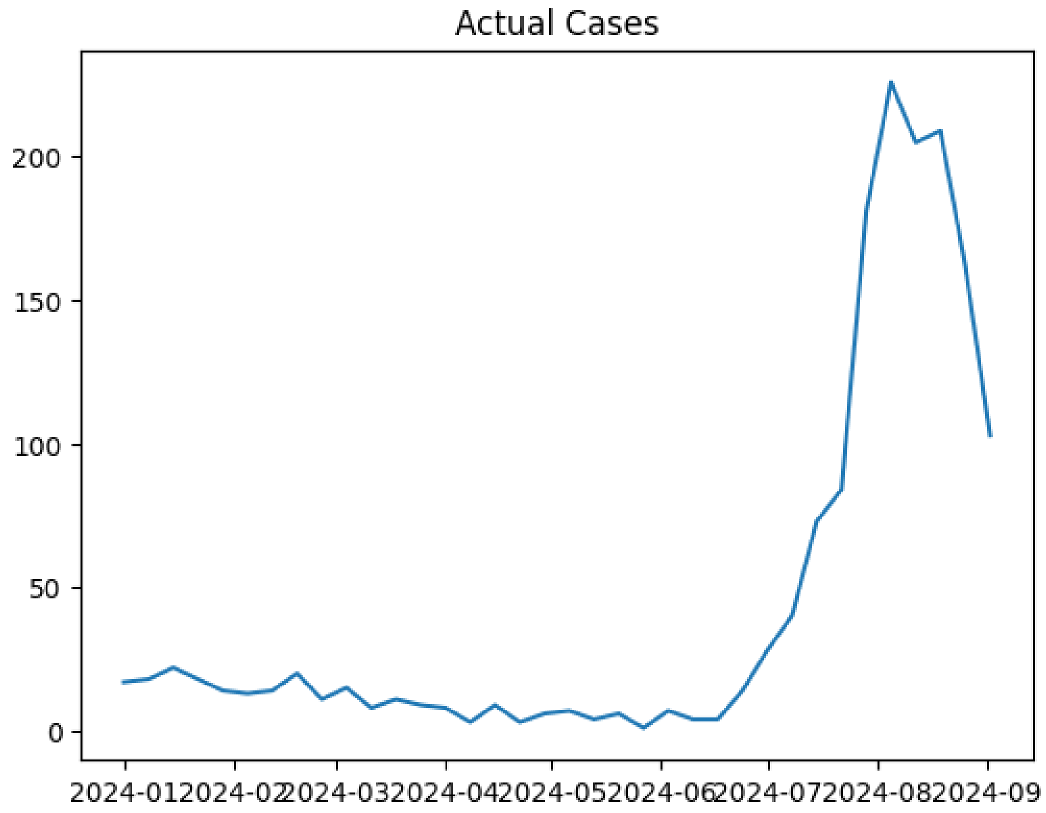
[10]:

```
fig, ax = plt.subplots(1,2, figsize=(15,5))
ax[0].plot(date,prediction_1_week)
ax[0].set_title('Prediction For 1-week ahead Model')
ax[1].plot(date,prediction_4_week)
ax[1].set_title('Prediction For 4-week ahead Model')
plt.suptitle('Predictions For n-week ahead Models')
plt.show()
```



[11]:
```
actual_2024 = data[data['dt'].dt.year == 2024]
plt.plot(actual_2024['dt'], actual_2024['Cases'])
plt.plot()
plt.title('Actual Cases')
```

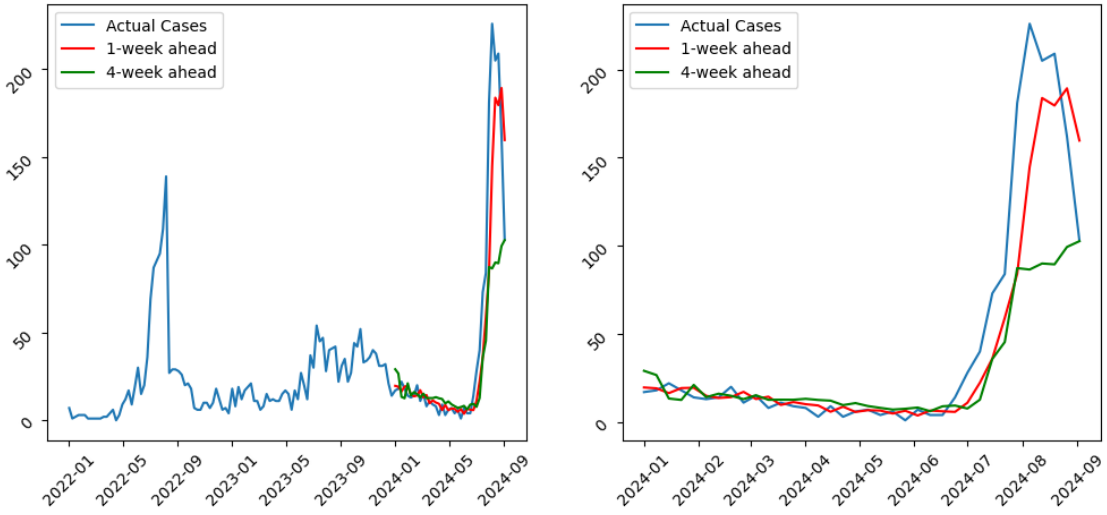
[11]:
```
Text(0.5, 1.0, 'Actual Cases')
```



[12]:

```
fig, ax = plt.subplots(1,2, figsize=(12,5))
ax[0].plot(data['dt'], data['Cases'], label = 'Actual Cases')
ax[0].plot(date, prediction_1_week, color = 'red', label = '1-week ahead')
ax[0].plot(date, prediction_4_week, color = 'green', label = '4-week ahead')
ax[0].tick_params(labelrotation=45)
ax[0].legend()
ax[1].plot(actual_2024['dt'], actual_2024['Cases'], label = 'Actual Cases')
ax[1].plot(date, prediction_1_week, color = 'red', label = '1-week ahead')
ax[1].plot(date, prediction_4_week, color = 'green', label = '4-week ahead')
ax[1].tick_params(labelrotation=45)
ax[1].legend()
plt.suptitle('Comparing Actual and predicted')
plt.show()
```

Comparing Actual and predicted



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