Our Mission

By making industry-leading tools and education available to individuals from all backgrounds, we level the playing field for future PM leaders. This is the PM Accelerator motto, as we grant aspiring and experienced PMs what they need most – Access. We introduce you to industry leaders, surround you with the right PM ecosystem, and discover the new world of AI product management skills.

Weather Forecasting

Objective

To analyze global weather data and build forecasting models to predict temperature trends, using traditional time-series methods.

Dataset Overview

Name: GlobalWeatherRepository.csv
Total Records: 62558
Total Columns: 41

	Column Name	Data Type
0	country	object
1	location_name	object
2	latitude	float64
3	longitude	float64
4	timezone	object
5	last_updated_epoch	int64
6	last_updated	object
7	temperature_celsius	float64
8	temperature_fahrenheit	float64
9	condition_text	object
10	wind_mph	float64
11	wind_kph	float64
12	wind_degree	int64
13	wind_direction	object
14	pressure_mb	float64
15	pressure_in	float64
16	precip_mm	float64
17	precip_in	float64
18	humidity	int64
19	cloud	int64
20	feels_like_celsius	float64

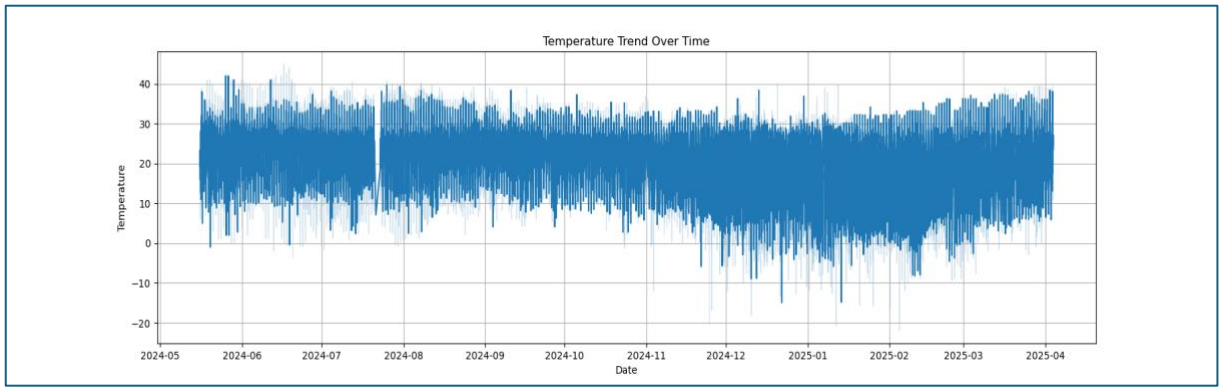
	Column Name	Data Type
21	feels_like_fahrenheit	float64
22	visibility_km	float64
23	visibility_miles	float64
24	uv_index	float64
25	gust_mph	float64
26	gust_kph	float64
27	air_quality_Carbon_Monoxide	float64
28	air_quality_Ozone	float64
29	air_quality_Nitrogen_dioxide	float64
30	air_quality_Sulphur_dioxide	float64
31	air_quality_PM2.5	float64
32	air_quality_PM10	float64
33	air_quality_us-epa-index	int64
34	air_quality_gb-defra-index	int64
35	sunrise	object
36	sunset	object
37	moonrise	object
38	moonset	object
39	moon_phase	object
40	moon_illumination	int64

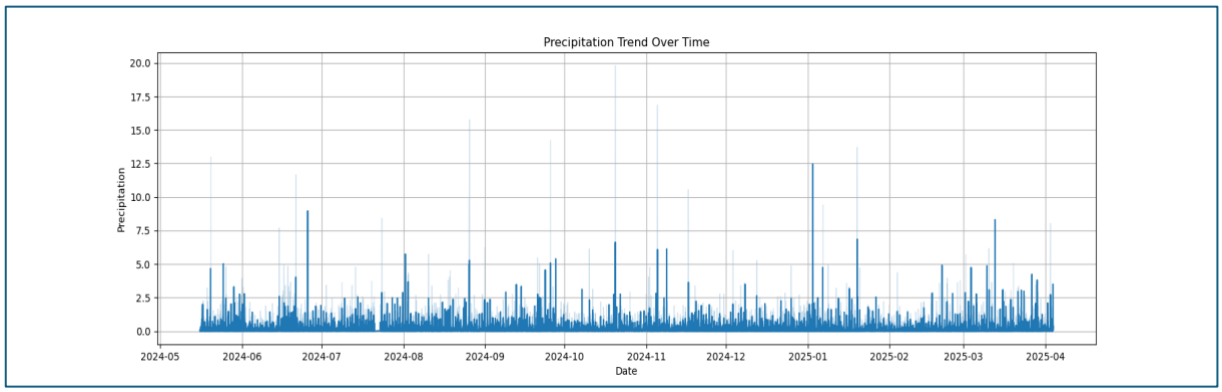
Data Cleaning & Preprocessing

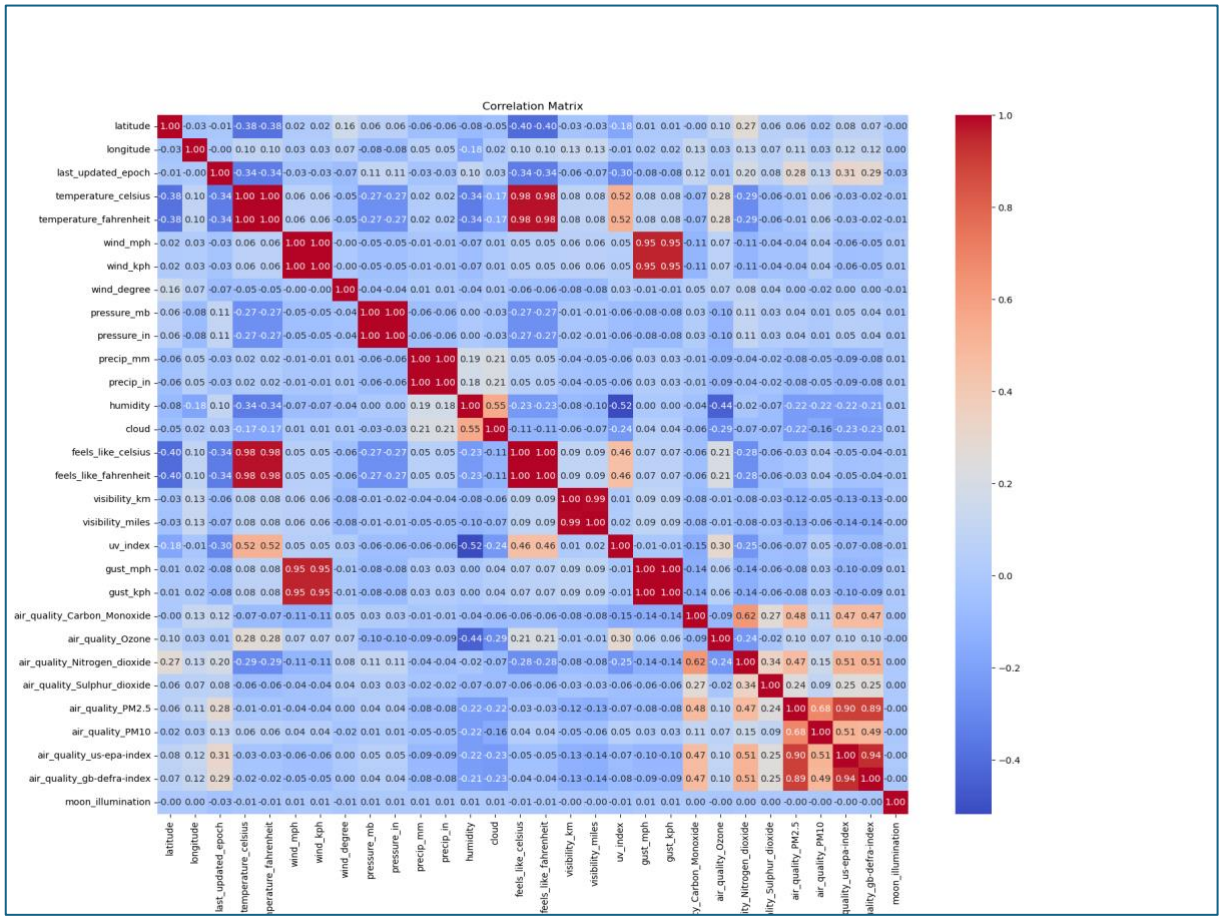
- No missing values are present in the dataset provided.
- The ‘IsolationForest’ algorithm is used to detect and remove outliers from numerical columns in the dataset.
- It assigns an "outlier" label (-1) to anomalous rows based on a contamination rate of 1% and filters them out, leaving only normal data points (1).
- The "outlier" column is then dropped to clean up the dataset.

Exploratory Data Analysis

- Analyzed correlations between various features like temperature, humidity, wind, precipitation, pressure etc.
- Visualized trends in temperature and precipitation over time
- Visualized weather differences across countries


Temperature Trend Over Time
Temperature
Date
40
30
20
10
0
−10
−20
2024-05
2024-06
2024-07
2024-08
2024-09
2024-10
2024-11
2024-12
2025-01
2025-02
2025-03
2025-04


Precipitation Trend Over Time
Precipitation
Date
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2024-05
2024-06
2024-07
2024-08
2024-09
2024-10
2024-11
2024-12
2025-01
2025-02
2025-03
2025-04


Correlation Matrix
latitude
longitude
last_updated_epoch
temperature_celsius
temperature_fahrenheit
wind_mph
wind_kph
wind_degree
pressure_mb
pressure_in
precip_mm
precip_in
humidity
cloud
feels_like_celsius
feels_like_fahrenheit
visibility_km
visibility_miles
uv_index
gust_mph
gust_kph
air_quality_Carbon_Monoxide
air_quality_Ozone
air_quality_Nitrogen_dioxide
air_quality_Sulphur_dioxide
air_quality_PM2.5
air_quality_PM10
air_quality_us-epa-index
air_quality_gb-defra-index
moon_illumination
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Forecasting with Multiple Models

Evaluation:

Model	MAE	MSE	RMSE	R^2 Score
ARIMA	6.9863	73.4687	8.5714	-0.0367
Facebook Prophet	6.5294	75.1736	8.6703	-0.0607
SARIMAX	9.9575	164.5829	12.8290	N/A
XGBoost Regressor	8.7602	96.4141	9.8191	-0.3604
Fine-Tuned XGBoost	0.0861	0.1770	0.4207	0.9983

Inference:

1. **ARIMA**:
   - Moderate performance with MAE of 6.9863 and RMSE of 8.5714.
   - Negative R^2 (-0.0367) indicates the model does not explain the variance in the data well, suggesting it struggles with capturing complex temporal patterns.

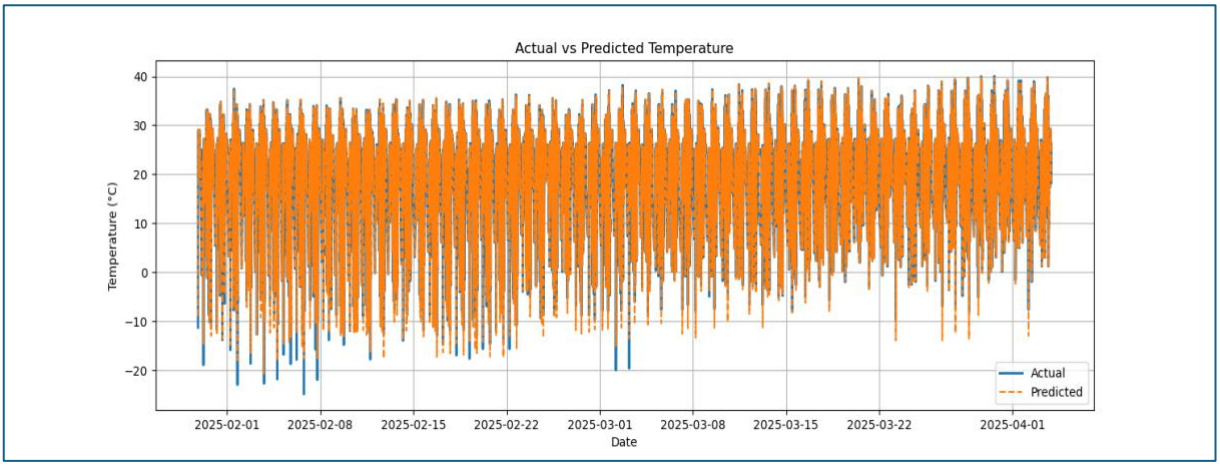
2. **Facebook Prophet**:
   - Slightly better MAE (6.5294) compared to ARIMA, but RMSE (8.6703) is slightly higher.
   - Negative R^2 (-0.0607) implies Prophet's seasonality handling is insufficient for this dataset, possibly due to noise or irregular patterns.

3. **SARIMAX**:
   - Poor performance with high MAE (9.9575) and RMSE (12.8290).
   - R^2 is not applicable, likely due to issues in model fitting or data resolution (e.g., monthly aggregation).

4. **XGBoost Regressor**:
   - MAE (8.7602) and RMSE (9.8191) indicate suboptimal predictions compared to ARIMA and Prophet.
   - R^2 (-0.3604) suggests overfitting or poor feature engineering in the initial implementation.

5. **Fine-Tuned XGBoost**:
   - Exceptional improvement with MAE (0.0861), RMSE (0.4207), and near-perfect R^2 (0.9983).
   - Indicates effective hyperparameter tuning and feature engineering, making it the best-performing model by far.

Fine-Tuned XGBoost Model



- Temporal features and lag features are created to capture trends and dependencies in the data.
- The target and feature variables are separated, and the dataset is split into training and testing sets.
- The XGBoost Model is trained using hyperparameter tuning with randomized search to optimize its performance on predicting temperature.
- 'RandomizedSearchCV' performs hyperparameter tuning by sampling random combinations from the hyperparameter space defined in params.
- The hyperparameters that will be tuned during the 'RandomizedSearchCV' are:
    - **n_estimators**: Number of boosting rounds or trees.
    - **max_depth**: Maximum depth of each tree.
    - **learning_rate**: The step size for each iteration.
    - **subsample**: Fraction of samples used for training each tree (used for regularization).
    - **colsample_bytree**: Fraction of features used for training each tree.
- The best model is used to make predictions on the test data.