Global Weather Forecasting Analysis & Prediction

TEMPERATURE PREDICTION MODEL USING TIME SERIES ANALYSIS WILSON ZHENG

PM Accelerator's 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.

Predicting temperature patterns using time series analysis

Dataset: Global Weather Repository (~58,270 entries from May 2024 to March 2025)

Focus: Temperature forecasting for the United States

Approach: SARIMA time series modeling with exogenous variables

Methodology

Data Cleaning & Preprocessing

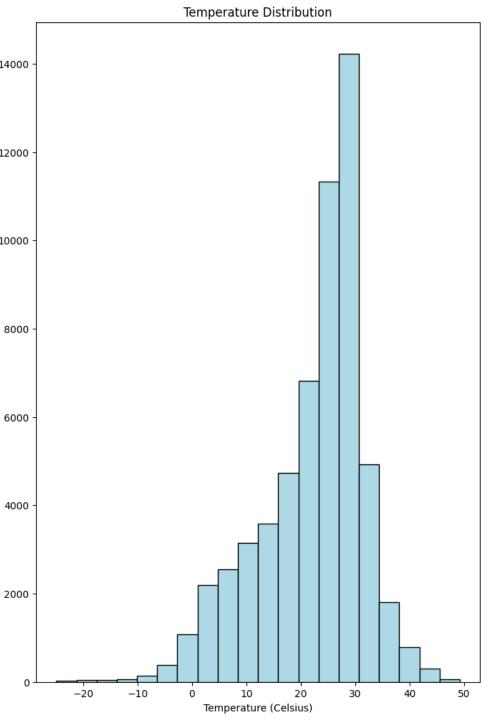
- Libraries: Pandas, NumPy
- Handling missing values (found none in the dataset)
- Outlier management using IQR method
- Feature selection and redundancy removal

Exploratory Data Analysis

- Libraries: seaborn, matplotlib
- Uncovering distributions, trends, and correlations in weather data
- Visualizing temperature and precipitation patterns

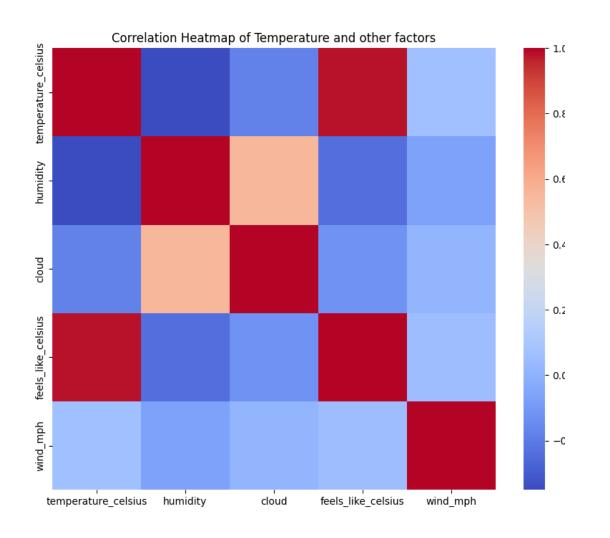
Model Building

- Libraries: pmdarima, statsmodels
- Time series forecasting with SARIMA
- Auto_arima for automated parameter selection
- Performance evaluation with RMSE



Exploratory Data Analysis

TEMPERATURE DISTRIBUTION HISTOGRAM WITH KEY FINDING: MOST FREQUENT TEMPERATURES BETWEEN 25-30°C



Correlation heatmap highlighting key relationships

Correlation heatmap highlighting key relationships:

Strong correlation between actual and feels-like temperature

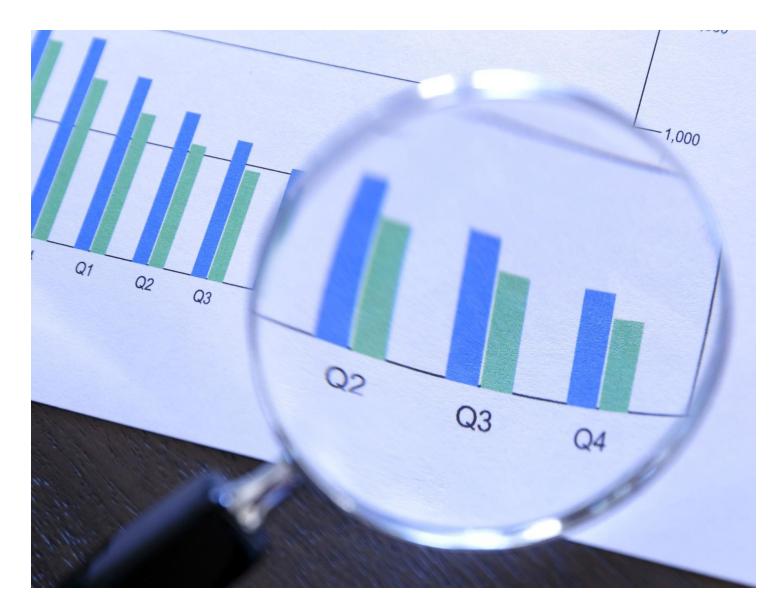
Weak negative correlation between humidity and temperature

Minimal correlation between other variables

Precipitation Distribution Frequency Precipitation (mm)

Precipitation insight

VERY LOW
PRECIPITATION
FREQUENCY (0.05% OF MEASUREMENTS)

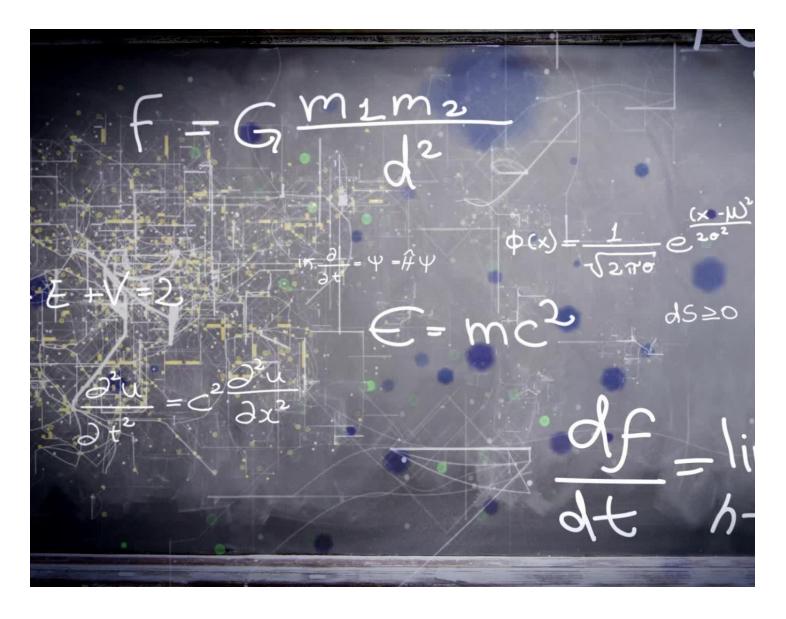


Data Preprocessing

Country selection: United States of America

Preprocessing pipeline:

- DateTime conversion and indexing using 'last_updated' column
- Feature reduction from 41 to 6 key features
- Outlier removal using IQR method
- Daily resampling and forward filling
- Final dataset: 301 daily observations ready for modeling



Model Training

Approach: SARIMA

Model selection process:

- Auto_arima library for optimal parameter identification
- First-order differencing for stationarity
- 80/20 train-test split

Key variables:

- Target: temperature_celsius
- Features: wind_kph, wind_degree, pressure_mb, humidity, gust_kph

Forecast vs. actual temperature visualization from the test set

Performance metric: RMSE = 4.04°C

Results & Evaluation

Residual analysis:

- -Random distribution indicating good model fit
- -Near-normal distribution with slight left skew
- -Interpretation: Model captures general trends but struggles with some fluctuations

Insights & Next Steps

Key insights:

- Weather patterns show complex dependencies
- Model achieves moderate prediction accuracy

Limitations:

- Limited dataset size after filtering (~300 entries)
- 10-month timeframe insufficient for full seasonal analysis

Future work:

- Expand data collection timeframe
- Incorporate additional variables
- Explore region-specific models