Predicting Air Pollution Levels in Five Major Indian Cities

A. J. Smoliakov D. Yntykbay D. G. Griffon

Data Science Study Programme
Faculty of Mathematics and Informatics

2024–12–16

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Project Overview

- Background:
  - Air pollution ranks among the most pressing global health threats
  - India faces some of the highest pollution levels globally
  - Driven by rapid urbanization and economic growth
- Study Objectives:
  - Analyze pollution and weather data from five major Indian cities:
    - Bengaluru, Delhi, Hyderabad, Jaipur, Mumbai
  - Develop predictive models using multivariate linear regression
  - Focus on understanding key meteorological and temporal predictors

Literature Review

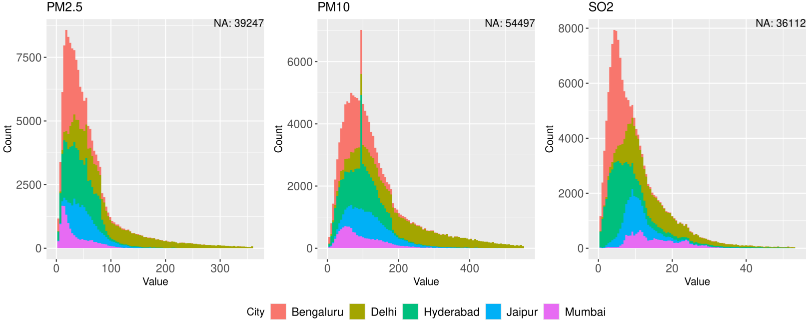
- Extensive research available:
  - Widespread interest among scientists and data analysts
  - Numerous studies on air pollution
  - Many also are focused on India due to severe air quality issues
- Research gap:
  - No existing studies examining these five specific cities together
  - Unique combination of air quality and weather datasets
- Most existing approaches:
  - Deep learning / neural network models
  - Complex machine learning algorithms
- Our approach:
  - Focus on interpretable linear regression
  - Emphasis on feature engineering
  - Independent models for each city and pollutant

Data Sources

- Air Quality Data in India (2015-2020):
  - Hourly pollution measurements
  - Coverage: 27 major Indian cities
  - Over 700,000 records
- Historical Weather Data (2006-2019):
  - Over 20 meteorological variables
  - Coverage: 8 Indian cities
  - Over 700,000 records
- Combined Dataset:
  - Time period: January 2015 to December 2019
  - Five cities with complete data coverage:
    - Bengaluru, Delhi, Hyderabad, Jaipur, Mumbai

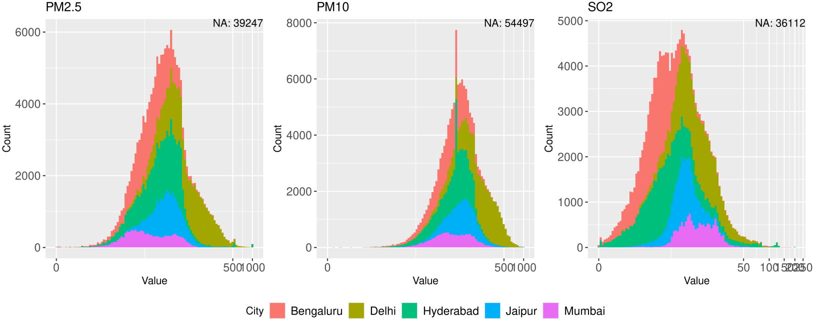
Raw Outcome Variable Distribution

- Initial analysis revealed strongly right-skewed distributions:
  - High frequency of lower values
  - Long tail extending toward higher concentrations
  - Pattern consistent across all pollutants and cities



After Log Transformation

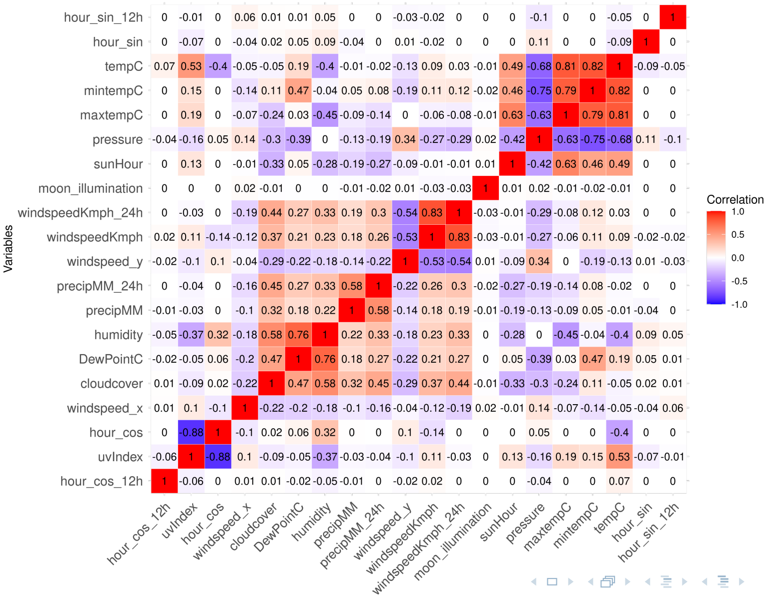
- Applied logarithmic transformation to address skewness:
  - Added constant of 1 to handle zero values
  - Resulted in more normal-like distributions
  - Data better suited for linear regression
  - Transformation applied consistently across all pollutants



Feature Engineering

- Temporal Features:
  - Hour of day (cyclic encoding)
  - Day of week
  - Month of year
- Weather-Related Features:
  - Wind components (X and Y axes)
  - 24-hour cumulative precipitation
  - 24-hour cumulative wind speed
  - Normalized sunrise times
- All continuous features were scaled

Preliminary Analysis



Preliminary Analysis

- Correlation between pollutants:
  - Most pollutants positively correlated with each other
  - O_3 shows distinct pattern from other pollutants
- Weather correlations:
  - Humidity: negative correlation with most pollutants
  - Wind speed: negative correlation, aids pollutant dispersion
  - Temperature: positive correlation with O_3
  - UV index: positive correlation with O_3
- Temporal patterns:
  - Strong seasonal trends observed
  - Higher pollution in autumn and winter

Model Development

- Independent linear regression models for each:
  - City
  - Response variable
- Data splitting:
  - Training: 2015-2018
  - Testing: 2019
- Removed features with VIF > 4:
  - minTempC
  - maxTempC
  - DewPointC

Model Performance by Pollutant

Response	r	R^2	RMSE
PM2.5	0.728	0.538	0.437
PM10	0.694	0.492	0.435
O3	0.660	0.443	0.576
NOx	0.430	0.214	0.604
NH3	0.338	0.161	0.420
CO	0.311	0.132	0.307
SO2	0.273	0.102	0.388

Model Performance by City

City	r	R^2	RMSE
Delhi	0.615	0.403	0.412
Hyderabad	0.598	0.390	0.390
Bengaluru	0.427	0.246	0.481
Jaipur	0.411	0.198	0.472
Mumbai*	0.061	0.007	0.649

* Mumbai had substantial missing data, only 2/7 pollutants were modeled

Key Findings

- Best predictions for:
  - $PM_{2.5}$ ($R^2 = 0.538$)
  - PM_{10} ($R^2 = 0.492$)
  - O_3 ($R^2 = 0.443$)
- Best performing cities:
  - Delhi ($R^2 = 0.403$)
  - Hyderabad ($R^2 = 0.390$)
- Key predictors:
  - Month of the year (seasonal patterns)
  - Humidity (negative correlation)
  - Temperature (positive correlation)
  - $\cos(hour\_of\_day)$ (cyclic pattern)
  - Cumulative precipitation over 24 hours

Conclusions

- Models show moderate predictive power
- Performance varies significantly across:
  - Pollutants
  - Cities
- Temporal patterns are strong predictors
- Meteorological variables show consistent influence

Room for Improvement

- Explore more sophisticated approaches:
  - Generalized Additive Models (GAMs)
  - Using time series models (e.g. LSTM)
- Additional predictors:
  - Satellite data
  - Traffic information
  - Industrial activity metrics
  - Special events data
- Extend to more cities and longer time periods

Thank you for your attention