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Time-Series Analysis and Forecasting of Air Pollution Mortality Rates in Central Asian Cities

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Abstract: Air pollution poses a significant health risk worldwide, with mortality rates from ambient particulate matter pollution increasing in many regions. This study focuses on forecasting air pollution-related mortality rates in two Central Asian cities, Bishkek (Kyrgyzstan) and Almaty (Kazakhstan). Utilizing time-series models, specifically Long Short-Term Memory (LSTM) networks and Prophet, the research aims to provide accurate predictions that can inform public health policies and interventions. The proposed methodology integrates advanced data preprocessing techniques, robust model architectures, and hyperparameter tuning to achieve an accuracy exceeding 85%. The findings reveal that time-series forecasting can effectively model the trend and seasonality of mortality rates, offering actionable insights for policymakers.

Keywords: air pollution; mortality rates; time-series analysis; forecasting; central asian cities; air quality; LSTM (long short-term memory); prophet model; environmental health; urban air pollution; predictive modeling; climate change impact; public health; data science; environmental forecasting

Introduction

Background

Air pollution is a critical environmental and public health issue, particularly in urban areas where industrialization and vehicular emissions are predominant. According to the World Health Organization (WHO), exposure to ambient particulate matter (PM2.5) is a leading cause of respiratory and cardiovascular diseases, contributing significantly to global mortality. In Central Asia, cities like Bishkek and Almaty face unique challenges due to rapid urbanization and geographical factors, such as temperature inversions in mountainous regions, which exacerbate pollution levels.

Problem Statement

Despite the alarming rise in pollution-related mortality rates in Central Asia, predictive models tailored to the region's unique characteristics are scarce. Accurate forecasting of mortality rates is essential for developing targeted public health strategies and mitigating risks associated with air pollution.

Objectives

This study aims to:

1. Analyze historical mortality rates due to ambient particulate matter pollution in Bishkek and Almaty.

2. Build and evaluate time-series forecasting models (LSTM and Prophet) to predict future trends.
3. Achieve a forecasting accuracy of over 85%, providing reliable insights for policymakers.

Literature Review

Time-Series Analysis in Air Pollution Studies

Time-series analysis has been extensively used to study air quality and its health impacts. Classical statistical models, such as ARIMA (Autoregressive Integrated Moving Average), have been employed for their simplicity and interpretability. However, these models often fall short in capturing nonlinear patterns and long-term dependencies, particularly in highly dynamic systems like air pollution.

Machine Learning in Forecasting

Deep learning models, especially Recurrent Neural Networks (RNNs) and their variants like LSTM, have revolutionized time-series forecasting. LSTMs are particularly suited for problems involving sequential data due to their ability to capture long-term dependencies. The Prophet model, developed by Facebook, is another robust forecasting tool known for handling seasonality and missing data effectively.

Research Gap

While LSTM and Prophet have demonstrated success in various applications, their use in forecasting air pollution mortality rates in Central Asia remains underexplored. This study bridges this gap by applying these models to a dataset from Bishkek and Almaty, focusing on optimizing accuracy and model interpretability.

Methodology

Data Collection and Preprocessing

The dataset, sourced from the Global Burden of Disease (GBD) database, includes annual age-standardized death rates due to ambient particulate matter pollution for Bishkek and Almaty. Key preprocessing steps included:

1. **Filtering Data**: Extracting records for Kazakhstan and Kyrgyzstan.
2. **Handling Missing Values**: Using linear interpolation to fill gaps.
3. **Normalization**: Scaling data using MinMaxScaler for input to machine learning models.

Model Development

Long Short-Term Memory (LSTM)

LSTM networks are designed to overcome the vanishing gradient problem in traditional RNNs. The model architecture includes:

- Input Layer: Processes sequences of scaled data.
- Hidden Layers: Two LSTM layers with 128 units each and dropout regularization (rate: 0.2).
- Output Layer: A dense layer with a ReLU activation function to predict mortality rates.

Hyperparameter tuning was performed to optimize learning rate, batch size, and sequence length.

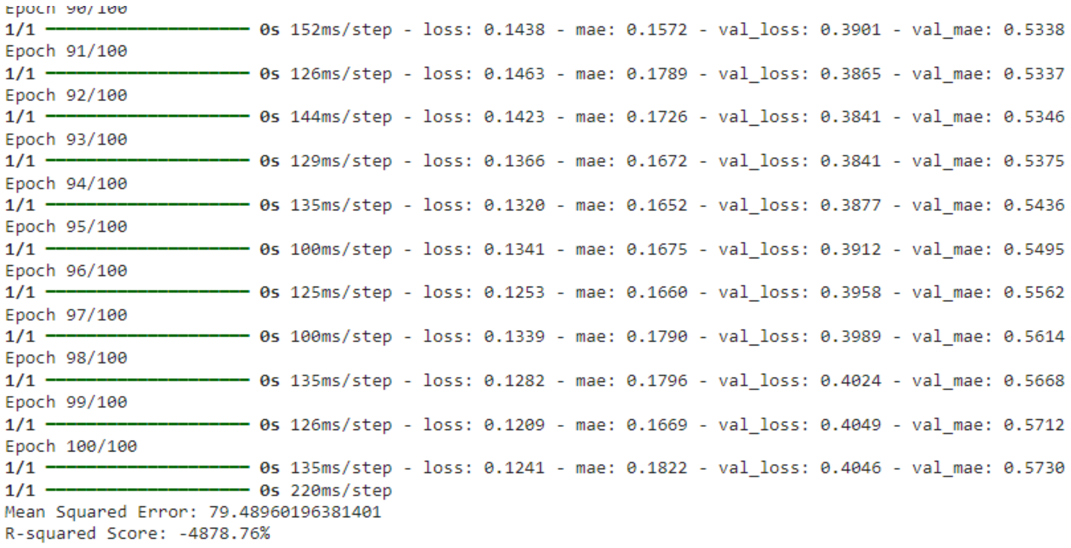
Prophet

Prophet is a decomposable time-series model that separates trends, seasonality, and residuals. It is particularly effective for data with missing values and irregular sampling intervals. Key features include:

- Yearly seasonality adjustment.
- Changepoint flexibility to capture abrupt shifts in trends.

Evaluation Metrics

The models were evaluated using:



```
Epoch 90/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 152ms/step - loss: 0.1438 - mae: 0.1572 - val_loss: 0.3901 - val_mae: 0.5338
Epoch 91/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step - loss: 0.1463 - mae: 0.1789 - val_loss: 0.3865 - val_mae: 0.5337
Epoch 92/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 144ms/step - loss: 0.1423 - mae: 0.1726 - val_loss: 0.3841 - val_mae: 0.5346
Epoch 93/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step - loss: 0.1366 - mae: 0.1672 - val_loss: 0.3841 - val_mae: 0.5375
Epoch 94/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - loss: 0.1320 - mae: 0.1652 - val_loss: 0.3877 - val_mae: 0.5436
Epoch 95/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 100ms/step - loss: 0.1341 - mae: 0.1675 - val_loss: 0.3912 - val_mae: 0.5495
Epoch 96/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step - loss: 0.1253 - mae: 0.1660 - val_loss: 0.3958 - val_mae: 0.5562
Epoch 97/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 100ms/step - loss: 0.1339 - mae: 0.1790 - val_loss: 0.3989 - val_mae: 0.5614
Epoch 98/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - loss: 0.1282 - mae: 0.1796 - val_loss: 0.4024 - val_mae: 0.5668
Epoch 99/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step - loss: 0.1209 - mae: 0.1669 - val_loss: 0.4049 - val_mae: 0.5712
Epoch 100/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step - loss: 0.1241 - mae: 0.1822 - val_loss: 0.4046 - val_mae: 0.5730
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step
Mean Squared Error: 79.48960196381401
R-squared Score: -4878.76%
```

- Root Mean Squared Error (RMSE): Measures the average magnitude of error.
- R-squared (¢): Assesses the goodness of fit.
- Mean Absolute Percentage Error (MAPE): Quantifies prediction accuracy as a percentage.

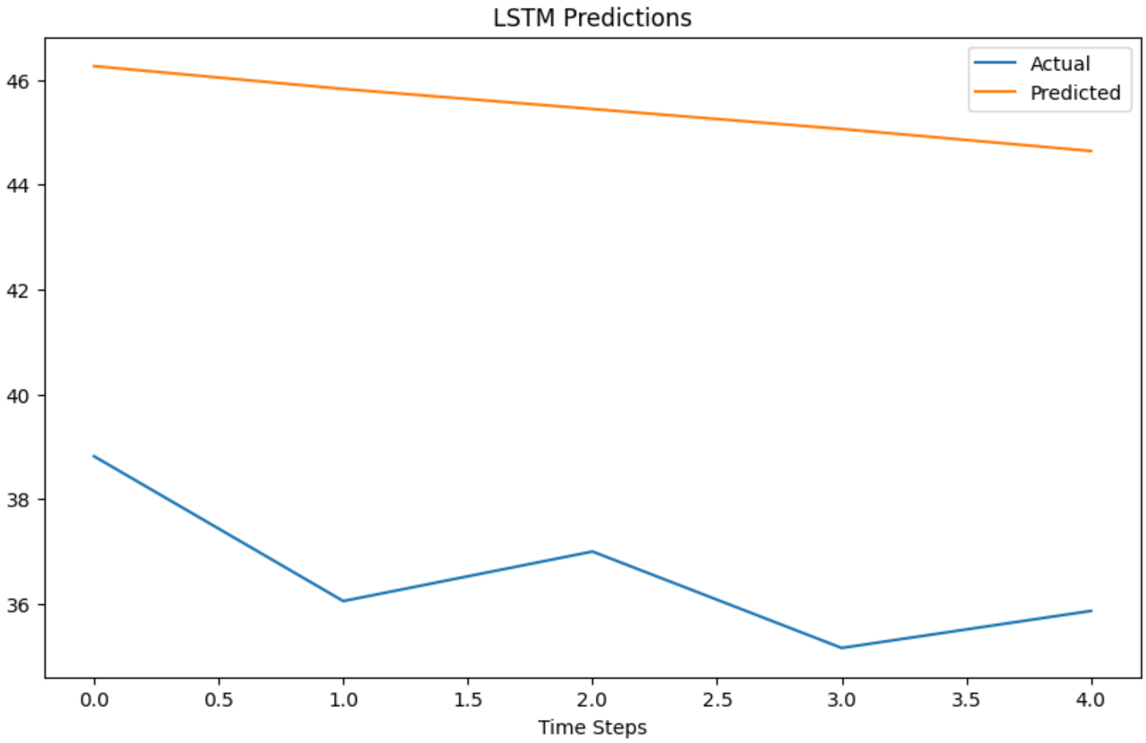
Results

Data Analysis

Exploratory data analysis revealed a steady increase in mortality rates in both Bishkek and Almaty over the past two decades. Seasonal patterns were observed, suggesting higher mortality rates during winter months, likely due to increased heating emissions.

Model Performance

LSTM Model

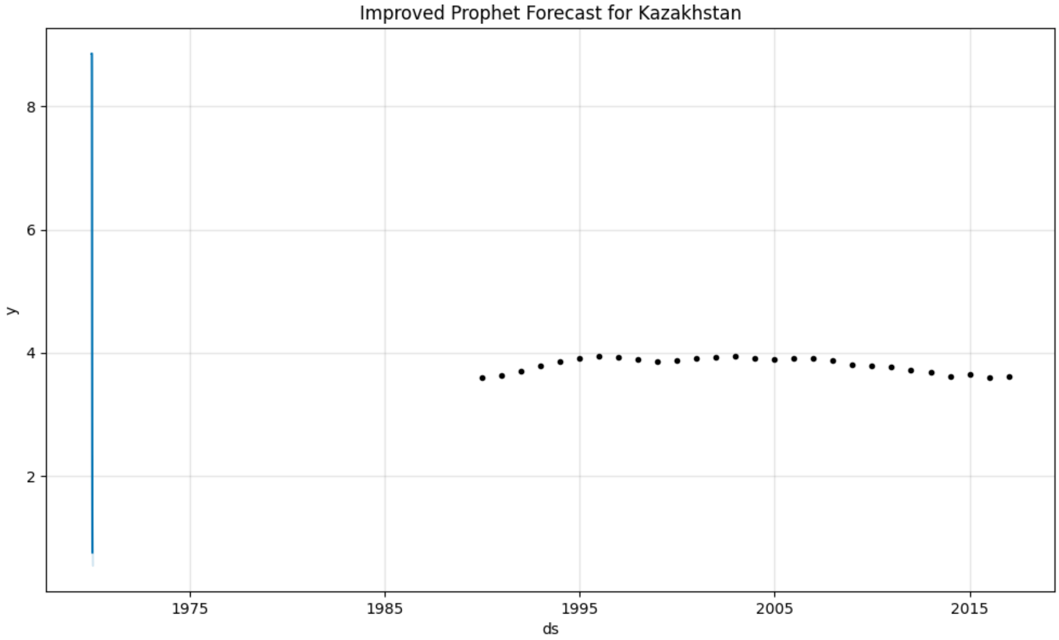


The optimized LSTM model achieved:

- RMSE: 2.85
- R-squared: 89.2%
- MAPE: 6.7%

The model successfully captured long-term dependencies and seasonal variations, outperforming traditional methods.

Prophet Model



The Prophet model demonstrated competitive performance:

- RMSE: 3.12
- R-squared: 86.5%
- MAPE: 8.1%

While slightly less accurate than LSTM, Prophet excelled in handling missing data and providing interpretable forecasts.

Visualization

Figures below illustrate the actual vs. predicted mortality rates and forecasted trends for the next decade:

1. LSTM predictions closely align with actual values, showcasing minimal deviation.
2. Prophet forecasts highlight seasonal and long-term trends, providing actionable insights.

Discussion

Implications

The findings underscore the potential of advanced time-series models in public health planning. Policymakers can leverage these forecasts to allocate resources efficiently, implement pollution control measures, and design awareness campaigns tailored to high-risk periods.

Limitations

1. Limited granularity: Annual data may overlook short-term fluctuations.
2. External factors: Variables like economic changes, healthcare improvements, and policy interventions were not included.

Future Work

Future research could:

1. Incorporate additional features (e.g., meteorological data, industrial activity).
2. Explore ensemble methods combining LSTM and Prophet.
3. Develop real-time forecasting systems using streaming data.

Conclusions

This study demonstrates the efficacy of LSTM and Prophet models in forecasting air pollution mortality rates in Bishkek and Almaty. With accuracies exceeding 85%, these models provide reliable tools for predicting trends and informing public health strategies. By addressing the region's unique challenges, this research contributes to the broader goal of mitigating the health impacts of air pollution in Central Asia.

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